ABSTRACT

CHOI, INCHUL. A Sensorimotor Rhythm (SMR)-Based Brain-Computer Interface (BCI) Controlled Functional Electrical Stimulation (FES) for Restoration of Hand Grasping and Extension Functions. (Under the direction of Dr. Chang S. Nam.)

Each year, 795,000 stroke patients suffer a new or recurrent stroke and 235,000 severe Traumatic Brain Injuries (TBIs) occur in the US. These patients are susceptible to a combination of significant motor, sensory, and cognitive deficits, and it becomes difficult or impossible for them to perform activities of daily living due to residual functional impairments. Recently, Sensorimotor Rhythm (SMR)-based Brain-Computer Interface (BCI) controlled Functional Electrical Stimulation (FES) has been studied for restoration and rehabilitation of motor deficits. However, there are some central issues in current studies as follows: Unclear guidelines to identify adequate FES electrode placement and parameters; unstructured Motor Imagery (MI) training procedures; lack of studies to classify different MI tasks in a single hand, such as grasping and opening; and difficulty in decoding voluntary MI-evoked SMRs (voluntary) compared to FES-driven passive-movement-evoked SMRs (passive).

This research tried to address these issues by proposing a novel SMR-based BCI-controlled FES system with 2-class MI tasks in a single hand, and investigated the feasibility of the proposed system with stroke and TBI patients.

The objectives of Study 1 were to realize natural hand-wrist motions and to improve user satisfaction by developing an FES platform. In Study 1, FES units with real-time computer-controlled functionality were built; appropriate initial FES electrode coordinates were provided with respect to anthropometric data; and a systematic procedure was proposed

to identify user-specific FES parameters. The post-hoc analysis revealed the scores of some FES parameters were significantly lower than that of the fixed parameters (pulse rate = 35 Hz; pulse width = 220 μs). It implied that the application of the user-specific FES parameters can decrease perceived muscle pain and discomfort, and, consequently, help to increase user satisfaction.

The objective of Study 2 was to propose a novel SMR-based BCI with visual guidance for (1) classifying 2-class MI tasks; (2) distinguishing voluntary and passive SMRs; and (3) identifying the best classification method. Participants were asked to mentally mimic visual guidance representing two different rhythmic MIs in synchronous experiments. The results showed that the accuracy of classifying 2-class MIs (~71.25%) was significantly higher than the true chance level, while that of distinguishing voluntary and passive SMRs was not. Furthermore, the standardized accuracies between three classification methods were significantly different, and the ensemble method showed significantly higher accuracy than linear discriminant analysis.

In Study 3, the patients performed goal-oriented tasks in semi-asynchronous experiments to validate the feasibility of the proposed system, and to evaluate the effects of the FES existence type and adaptive learning on task performance. The results showed the application of adaptive learning significantly increased the accuracy, and the accuracy after applying adaptive learning under the No-FES condition (61.9%) was significantly higher than the true chance level. In addition, subjective mental workloads were compared between the two experiments. The results revealed that mental demand and frustration significantly

increased, while performance significantly decreased during semi-asynchronous experiment compared to synchronous experiment.

This study was expected to provide fundamental knowledge of BCI-FES studies, such as adequate initial FES electrode coordinates, user-specific FES parameter setting procedures, and the novel rhythmic MI tasks for classifying 2-class MIs in a single hand. Moreover, the proposed system can be used as a testbed to investigate important human factors/ergonomics topics, such as the effects of individual differences and environmental factors on task performance and user satisfaction. Finally, the results of this research can also be utilized to gain an understanding of neuroplasticity in rehabilitation of stroke and TBI patients in clinical studies.

A Sensorimotor Rhythm (SMR)-Based Brain-Computer Interface (BCI) Controlled Functional Electrical Stimulation (FES) for Restoration of Hand Grasping and Extension Functions

by
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DEDICATION

I dedicate my dissertation to my wife, Soyoung Kim, and lovely daughter, Hana, whose boundless support, patience, and encouragement helped me throughout my studies. I am truly thankful to have you in my life.

A special thank you to my beloved parents, Taehyun Choi and Youngju Yeo, who have always loved me unconditionally. I also dedicate this dissertation to my brother Inhan Choi, sister-in-law Kwia Lee, and my parents-in-law who have never left my side.

BIOGRAPHY

Inchul Choi was born on May 31, 1979 in Seoul, Korea. After graduating from Yeouido High School (1998), Inchul attended Hongik University with a B.S. in Industrial Engineering. Upon graduating from Hongik, Inchul worked as a sales consultant and representative at Samsung Electronics in Korea for more than four years. In 2010, Inchul pursued a M.S. in Industrial Engineering at Hongik University under the advisement of Dr. Chang-Soo Ok. Upon completion of his M.S., Inchul began a doctorate program in Industrial and Systems Engineering at North Carolina State University in 2012 under the guidance of Dr. Chang S. Nam. His research interests focus on brain signal processing, machine learning, and the design of brain-computer interfaces for understanding and helping the disabled population.

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I. Choi, K. Bond, & C. Nam. "A Hybrid BCI-Controlled FES System for Hand-Wrist Motor Function" IEEE SMC, 2016.

I. Choi, K. Bond, D. Krusienski, & C. Nam. "Effects of Off-Site Attention on SSSEP Amplitude." Proceedings of the Sixth International Brain-Computer Interface Meeting, 2016.

I. Choi, K. Bond, D. Krusienski, & C. Nam. "Comparison of Stimulation Patterns to Elicit Steady-State Somatosensory Evoked Potentials (SSSEPs): Implications for Hybrid and SSSEP-Based BCIs." IEEE SMC, 2015.

C. Nam, M. Moore, **I. Choi**, Y. Li, & J. Lee. "Designing Better, Cost-Effective Brain-Computer Interfaces." Ergonomics in Design: The Quarterly of Human Factors Applications, 2015, 23(4), 13-19.

C. Nam, J. Lee, S. Bahn, Y. Li, & **I. Choi**. "Brain-Computer Interface Supported Collaborative Work." Proceedings of the Fifth International Brain-Computer Interface Meeting, 2013.

LIST OF ACRONYMS

ADLs	Activities of Daily Living
ANOVA	Analysis of Variance
BCI	Brain-Computer Interface
CSP	Common Spatial Pattern
DF	Degrees of Freedom
DV	Dependent Variable
EEG	Electroencephalography
EMG	Electromyography
ERD/ERS	Event-Related Desynchronization and Synchronization
ERP	Event-Related Potential
ERSP	Event-Related Spectral Perturbation
FCO	Fast Cyclic Opening
FE	Finger Extension
FES	Functional Electrical Simulation
FF	Finger Flexion
FFT	Fast Fourier Transform
HF/E	Human Factors and Ergonomics
HSD	Honest Significant Difference
ICA	Independent Component Analysis
ITR	Information Transfer Rate
IV	Independent Variable
LDA	Linear Discriminant Analysis
MI	Motor Imagery
NASA-TLX	NASA-Task Load Index
PC	Personal Computer
PCA	Principal Component Analysis
PMean	Pooled Mean

PPV	Positive Predictive Value
PSD	Power Spectral Density
SBCSP	Sub-band Common Spatial Pattern
SMR	Sensorimotor Rhythm
SOG	Slow One-time Grasping
STD	Standard Deviation
SVM	Support Vector Machine
TBI	Traumatic Brain Injury
TENS	Transcutaneous Electrical Nerve Stimulation
VAS	Visual Analogue Scale
WE	Wrist Extension
WF	Wrist Flexion

LIST OF ACRONYMS FOR BONE AND MUSCLE

ECRB	Extensor Carpi Radialis Brevis
ECRL	Extensor Carpi Radialis Longus
ECU	Extensor Carpi Ulnaris
EDC	Extensor Digitorum Communis
EPB	Extensor Pollicis Brevis
EPL	Extensor Pollicis Longus
FCR	Flexor Carpi Radialis
FCU	Flexor Carpi Ulnaris
FDP	Flexor Digitorum Profundus
FDS	Flexor Digitorum Superficialis
FPL	Flexor Pollicis Longus
PL	Palmaris Longus
PQ	Pronator Quadratus
PT	Pronator Teres
USP	Ulnar Styloid Process
RSP	Radial Styloid Process

1. INTRODUCTION

Healthy individuals whose brains and neuromuscular systems enable normal motor functions can naturally perform Activities of Daily Living (ADLs). Nonetheless, for some people who have disabilities in these functions due to injury or disease, simple tasks become very difficult or impossible to do. To assist this population, researchers in many fields, from physical therapy to engineering, have developed various rehabilitation technologies that help them perform ADLs (van Delden, Peper, Kwakkel, & Beek, 2012; Iosa, Hesse, Oliviero, & Paolucci, 2013; Loureiro, Harwin, Nagai, & Johnson, 2011). One such technology, Functional Electrical Stimulation (FES), delivers electrical impulses to either paralyzed or impaired limbs to generate artificial muscle contraction (Peckham & Knutson, 2005; Sujith, 2008). In this way, FES helps disabled people perform ADLs such as walking, reaching, and grasping (Johnson & Fuglevand, 2011; Popovic, Curt, Keller, & Dietz, 2001). Some FES devices are controlled by Brain-Computer Interfaces (BCIs), sometimes called brain-machine interfaces.

In general, BCIs can help people communicate and control devices and applications without using peripheral nerves and muscle pathways (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). BCIs are also a potential method to promote the independence of physically disabled people by means of the BCIs' ability to bypass non-functional neural pathways (Daly & Wolpaw, 2008). A Sensorimotor Rhythm (SMR)-based BCI-controlled FES system is a novel technology that combines the advantages of FES and BCI systems, and allows severely disabled patients to restore motor functions through the FES system by translating voluntary Motor Imagery (MI) to physical action (Pfurtscheller et al., 2003). There are many potential benefits of combining SMR-based BCIs and FES systems,

such as the promotion of neuroplasticity (McGie, Zariffa, Popovic, & Nagai, 2015), the restoration of motor functions by using voluntary motor intentions (Pfurtscheller et al., 2003; Rohm, Muller-Putz, Kreilinger, von Ascheberg, & Rupp, 2010), and providing proprioceptive sensory feedback as a result of their intentions (Hara, 2008).

Although SMR-based BCI-controlled FES methods seem promising, current studies still have central issues: (1) unclear guidelines and procedures on how to place FES electrodes on proper muscles and how to set FES parameters for natural hand and wrist movements with minimum perceived muscle pain and discomfort; (2) ambiguous instruction of MI tasks during training under SMR-based BCI systems, and (3) difficulties in classifying voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs when FES is activated. Moreover, (4) only few studies have examined the feasibility of classifying two different MI tasks in a single hand, such as grasping and opening, and (5) few studies have examined human factors and ergonomics (HF/E) perspectives such as subjective mental workload and user satisfaction in the use of SMR-based BCI-controlled FES systems.

This study aims to address these issues by (1) building a customized FES platform that could reproduce real-time movements of natural hands and wrists through brain signals; (2) utilizing anthropometric data to provide appropriate initial FES electrode coordinates that could help in finding adequate FES electrode placement; (3) proposing a systematic procedure to identify user-specific FES parameters that could minimize perceived muscle pain and discomfort and, consequently, increase user satisfaction; (4) developing a novel SMR-based BCI system with visual guidance during training to classify a 2-class MI task in a single hand and to classify voluntary and passive SMRs, and (5) evaluating the feasibility of the proposed

BCI-controlled FES system by performing sequential goal-oriented tasks with stroke and TBI patients.

The following sections provide a brief introduction to the FES systems and SMR-based BCI systems for patients with stroke and TBI, and each section summarizes the limitations of current research studies. Thereafter, the objectives of this research study are outlined at the end of Chapter 1 (See Figure 1.1).

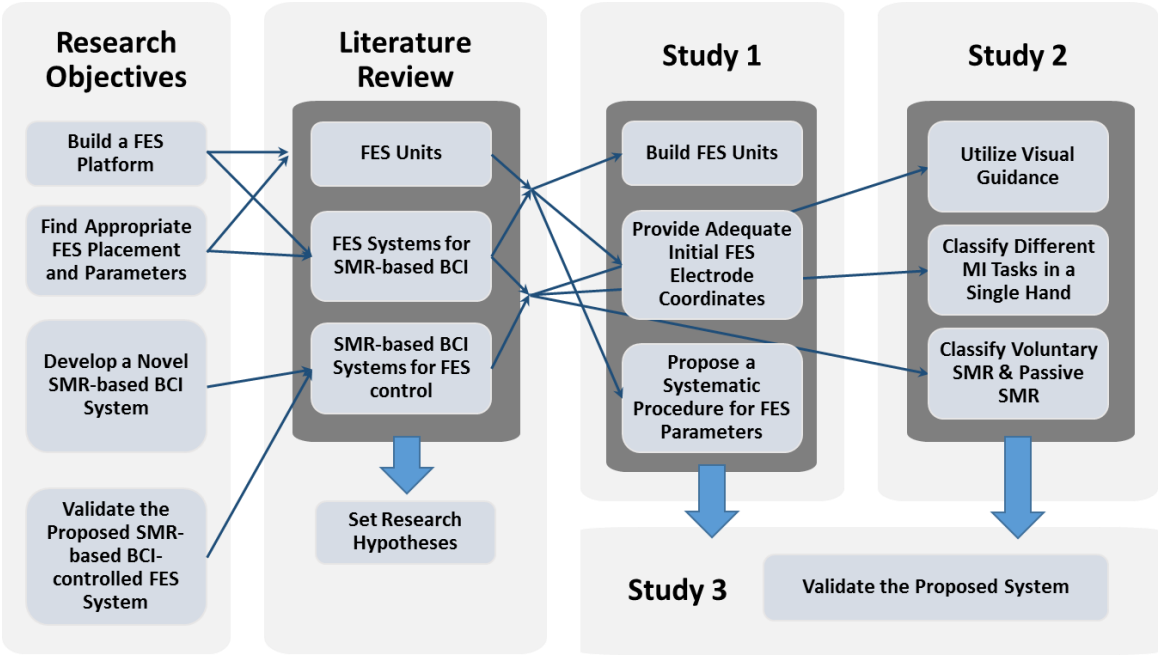


Figure 1.1. Research framework

Chapter 2 contains a survey of current FES systems and systematic literature reviews of SMR-based BCI studies for FES systems. This chapter identifies the limitations of current research and clarifies the current state of BCI-controlled FES technologies. Based on the survey and literature reviews, research questions and hypotheses were set according to the objectives of this research study at the end of Chapter 2.

Chapter 3 describes Study 1 consisting of two phases, in which the FES platform was developed (See Figure 1.2). The first phase demonstrated development of customized FES units, including the characteristics of FES parameters embodied in the proposed system and the ability to control FES parameters in real-time. In the second phase, FES electrode placement was determined by considering anthropometric data to provide adequate initial FES electrode placement. In addition, the user-specific FES parameters were identified by following a systematic parameter determination procedure to enhance user satisfaction. The results of this phase could help to identify appropriate initial FES electrode coordinates and three user-specific FES parameters to restore natural hand grasping and opening motions with minimum perceived muscle pain and discomfort.

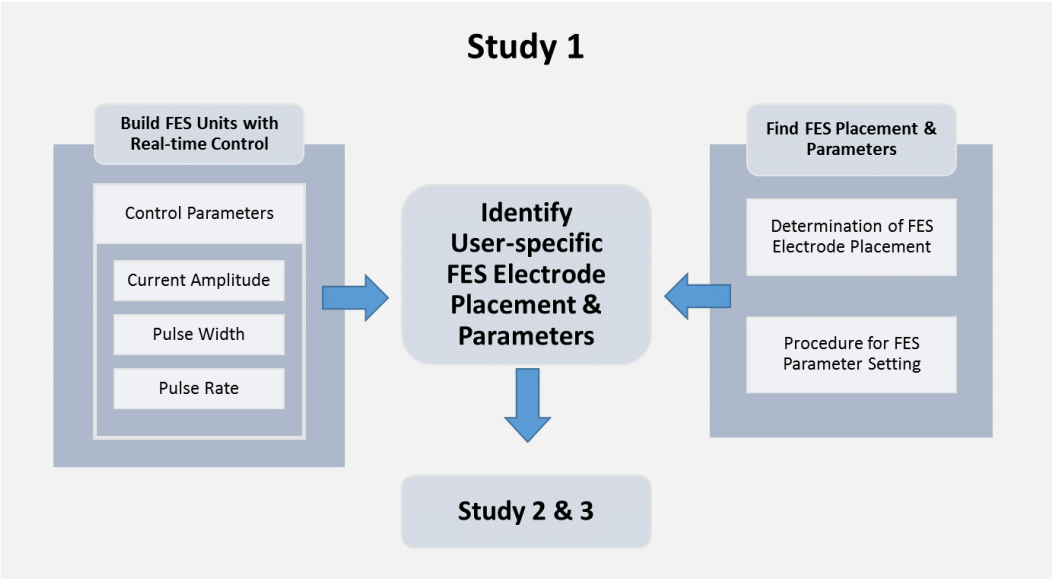


Figure 1.2. Framework of Study 1

In Chapter 4, Study 2, a novel SMR-based BCI system to control FES was proposed to address the issues on current research studies by (1) providing visual guidance during MI training; (2) utilizing two different rhythmic MI tasks, such as slow one-time grasping and fast cyclic opening, to classify a 2-class MI task in a single hand, and (3) decoding different SMR inducing types, such as voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs. After training, the user-specific classification algorithm parameters were identified according to three roles including (1) detecting SMR, (2) classifying a 2-class MI task, and (3) decoding voluntary and passive SMRs (See Figure 1.3).

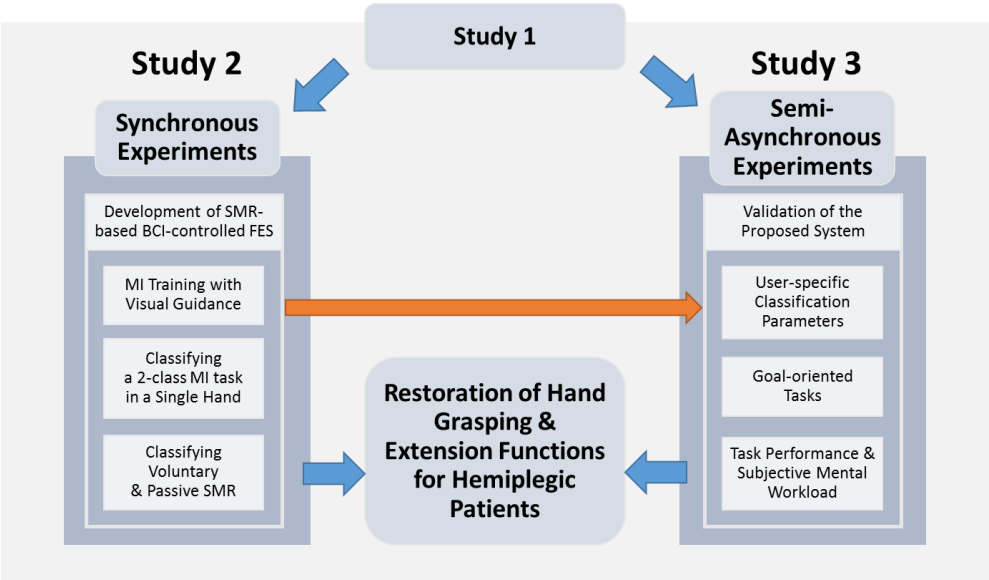


Figure 1.3. Framework of Studies 2 and 3

Chapter 5, Study 3, aims to validate the feasibility of the proposed BCI-FES system by conducting a sequential task with fixed order under a semi-asynchronous mode, and to analyze patient's task performance and subjective mental workload (See Figure 1.3). All experiments in this study were conducted in patients with hemiparesis.

1.1. How does FES work?

1.1.1. Stroke and Traumatic Brain Injury

Each year, more than 795,000 stroke patients suffer a new or recurrent stroke in the United States, and 33 million patients suffer strokes worldwide (Lloyd-Jones et al., 2009; Mozaffarian et al., 2015). In addition, 235,000 severe Traumatic Brain Injuries (TBI) occur in the United States each year, and there are 57 million TBIs worldwide (Hirtz et al., 2007; Langlois, Rutland-Brown, & Wald, 2006). Many of these patients are susceptible to a combination of significant motor, sensory, and cognitive deficits (Langlois et al., 2006; Pereira, Teasell, Graham, & Salter, 2013), and they experience residual functional impairments (Miller et al., 2010). For instance, 25% to 62% of stroke survivors and 77% of severe TBI patients suffer from major physical complications such as spasticity and muscle weakness (Hoofien, Gilboa, Vakil, & Donovick, 2001; Wallesch, Maes, Lecomte, & Bartels, 1997; Watkins et al., 2002; Wissel et al., 2010).

These neuromuscular disorders cause upper and/or lower extremity impairments, such as hemiparesis or hemiplegia, and hinder patients from performing ADLs naturally. For example, between 25% and 74% of the stroke survivors in the United States (roughly 6.6 million) and worldwide (over 50 million) remain partially or fully dependent on caregivers for ADLs (Miller et al., 2010; Patten, Lexell, & Brown, 2004). For this reason, many research studies and intervention methods for these patients have been attempted to aid motor rehabilitation - including physical, neurosurgical, and pharmacological treatments (DeJong, Horn, Conroy, Nichols, & Healton, 2005; Langhorne, Coupar, & Pollock, 2009; Miller et al., 2010). A combination of these rehabilitation techniques could be used for treatment, among

which physical therapy, including occupational therapy, is the most common and essential (Miller et al., 2010).

1.1.2. FES Rehabilitation for Stroke and TBI Patients

The physical treatments include repeated range-of-motion exercises (Duncan et al., 2005), thermotherapy (Matsumoto et al., 2010), and electrical stimulation (Kawashima, Popovic, & Zivanovic, 2013; Quandt & Hummel, 2014). Among these physical treatment methods for patients, FES is a common adjuvant therapy and has been widely adopted as a clinical application (Lynch & Popovic, 2008; Miller et al., 2010). Levin and Hui-Chan (1992) found that repeated electrical stimulation could reduce spasticity and improve motor functions in hemiparetic patients. Sabut and colleagues (2011) also reported that conventional rehabilitation (i.e., OT) with FES treatment showed better rehabilitation outcomes than OT alone, with respect to reducing spasticity and improving muscle strength and motor recovery in stroke patients.

FES systems also have unique strengths in restoring motor functions for hemiparetic patients (Zhang, Guan, Widjaja, & Ang, 2007). First, FES systems have advantages over customized orthoses and exoskeletons because they are lightweight and affordable, and universal in terms of the body shape and size of body parts they can accommodate (Kottink et al., 2004; Kralj & Grobelnik, 1973). Other advantages of FES treatment include the promotion of motor learning and neural reorganization (Jackson, Mavoori, & Fetz, 2006; Sujith, 2008). The importance of the FES treatment is that cortical activation could be facilitated by forcing the patients to practice with impaired extremities which patients do not tend to use due to

difficulties (Teasell, Bayona, & Bitensky, 2015; Wolf, 2007). Moreover, Papachristos (2014) identified the psychological benefits of utilizing FES rehabilitation, such as increasing self-esteem and reducing depression. Therefore, many research studies have been conducted with FES for motor function restoration of stroke and TBI patients (Chan, Tong, & Chung, 2009; Kawashima et al., 2013; Young, Williams, & Prabhakaran, 2014).

The FES methods can be applied to various body parts, such as the foot (Kottink et al., 2004; Sabut et al., 2011), shoulder and elbow (Aoyagi & Tsubahara, 2004; Chae, Sheffler, & Knutson, 2008), and forearm (Lawrence, 2009; Thrasher, Zivanovic, McIlroy, & Popovic, 2008). Among them, the restoration of hand function is one of the most important for patients' independence in performing ADLs such as feeding, dressing, bathing, and making transfers (Adams, Takes, Popovic, Bulsen, & Zivanovic, 2003; Mangold, Keller, Curt, & Dietz, 2005; Popovic, Popovic, & Keller, 2002). Further support for the importance of the hand function were found in Langhorne and colleagues' (2009) systematic review. The authors quantified the number of studies of each intervention target, and found 115 studies concerning hand and arm functions, as well as 9, 14, and 68 studies for sit-to-stand, standing balance, and gait rehabilitation for lower limbs, respectively.

The FES system can be activated by either push-button-control, cyclic programs, or the patient's effort (Doucet, Lam, & Griffin, 2012; McGie et al., 2015; Quandt & Hummel, 2014). However, when FES is controlled by either automated cyclic programs or physical therapists, the patient's intention and effort is decreased. This means that the restoration of motor functions is not directly involved in the central nervous system, but is passively initiated by other factors rather than a patient's effort. In this case, neuroplasticity of the patient, which is

important to benefit rehabilitation, may not be promoted well due to the lack of synchronization between a patient's effort and physiological feedback. Neuroplasticity occurs throughout the central nervous system (Daly & Wolpaw, 2008), and is defined as the ability of the human brain to alter its structure in response to environmental demands (Draganski et al., 2004). Many research studies show the evidence of a positive effect on rehabilitation outcomes when the patient's intentions are synchronized with the physiological feedback. Lourenção et al. (2008) showed that receiving OT and FES treatments with Electromyographic (EMG) biofeedback improved upper extremity function significantly more than receiving only OT and FES. Cauraugh and Kim (2002) utilized an EMG signal to synchronize the patient's motor intentions and FES, and they reported that the application of EMG-triggered electrical stimulation enhanced voluntary motor control of stroke patients more than that of electrical stimulation without utilizing EMG signal. Barsi et al. (2008) also found that the combination of voluntary motor effort and electrical stimulation was more effective compared to electrical stimulation or repetitive voluntary training alone in rehabilitation of stroke patients because it had a greater potential to promote plasticity in the motor cortex. For these reasons, Takahashi et al. (2012) suggested that the FES system should synchronize between motor intention and the electrical stimulation feedback to promote neuroplasticity.

1.1.3. Limitations of Current FES Studies

Although the EMG-triggered FES paradigms have many advantages, they also have shortcomings. First, EMG-triggered FES systems require the residual muscle activity of an affected limb. Therefore, these paradigms cannot be applied to severely disabled patients

whose EMG signals are not consistently measurable (Takahashi et al., 2012). Furthermore, EMG signals cannot be measured correctly when electrical stimulation is applied due to the higher electrical amplitude of FES than that of EMG signals (Hines, Crago, Chapman, & Billian, 1996; Minzly, Mizrahi, Hakim, & Liberson, 1993). This limitation precludes patients from utilizing EMG signals as a medium to stop or maintain the FES system when it is activated. For such patients and conditions, BCIs can be used as an alternative method to detect motor intention directly from the brain signal without residual muscle activities.

Additionally, most of the current research studies did not precisely define adequate FES electrode placement, or provide clear guidance which helps to identify appropriate electrode coordinates with respect to muscle groups. Lawrence (2009) measured the distances from styloid processes and epicondyles in the forearm to indicate the coordinates of the FES electrodes, but the other research studies vaguely described the name of the muscles where electrodes were placed on. Furthermore, only a few research studies had taken FES parameters into account that are important (1) to carry out natural muscle contraction, (2) to reduce perceived muscle pain and discomfort, and consequently (3) to enhance user satisfaction. Tan et al. (2011) proposed a muscle model with the weight and length of the forearm to determine the intensity of electrical stimulation for controlling forearm movement. Kesar and colleagues (2008) compared muscle performance with three different combinations of pulse rate and pulse width, and reported that constant pulse width and stepwise increases in pulse rate showed better performance of muscle contraction than fixed frequency and stepwise increments of pulse width or fixed pulse width and rate. Even though there exist few studies as above, more studies

need to be conducted to help researchers identify appropriate FES electrode placement and parameter combinations.

1.2. How does SMR-based BCI-controlled FES work?

1.2.1. What is a BCI?

BCIs can help people to communicate and control devices and applications without using peripheral nerves and muscle pathways (Wolpaw et al., 2002). BCIs are a potential method to promote the independence of disabled persons because of the BCIs' ability to bypass non-functional neural pathways (Daly & Wolpaw, 2008). Therefore, many researchers have endeavored to apply BCI technologies to assist disabled persons with severe neuromuscular impairments such as amyotrophic lateral sclerosis, cerebral palsy, spinal cord injury, persistent vegetative state, locked-in syndrome, TBI, and stroke complications (Brouwer & van Erp, 2010; Daly & Wolpaw, 2008; Mak & Wolpaw, 2009; Nijboer et al., 2008).

A wide variety of BCI systems have been developed for communication and control of assistive devices. For example, there are various types of BCI-spellers with visual, auditory, and even tactile stimuli to help patients communicate with the outside world (Brouwer & van Erp, 2010; Farwell & Donchin, 1988; Käthner et al., 2013; Klobassa et al., 2009; Pfurtscheller et al., 2008). To support patients' mobility and accessibility, a diverse set of BCI-controlled applications has been developed, such as BCI-controlled wheelchairs, orthoses, prostheses, and exoskeletons (Barsotti et al., 2015; Iturrate, Antelis, Kubler, & Minguez, 2009; Pfurtscheller et al., 2008; Pfurtscheller, Solis-Escalante, Ortner, Linortner, & Muller-Putz, 2010; Popovic et

al., 2002). Moreover, BCI-controlled robots, games, and even music and art applications were developed to improve their quality of life (Bell, Shenoy, Chalodhorn, & Rao, 2008; Finke, Lenhardt, & Ritter, 2009; Grierson, 2008; Holz, Botrel, & Kübler, 2015; Li & Nam, 2015; Nam, Lee, Bahn, Li, & Choi, 2014; Nam, Moore, Choi, & Li, 2015).

Brain imaging technologies to measure brain activity can be classified into two categories: non-invasive, such as electroencephalography (EEG), magnetoencephalographic, functional near-infrared spectroscopy, functional magnetic resonance imaging, and positron emission tomography; and invasive, such as implantable electrocorticography and intracortical neuron recording methods (Bhattacharyya, Khasnobish, Ghosh, Mazumder, & Tibarewala, 2015; Buch et al., 2008; Carpi, Rossi, & Menon, 2006; Ferrari & Quaresima, 2012; Homer, Nurmikko, Donoghue, & Hochberg, 2013; Schalk & Leuthardt, 2011; Weiskopf et al., 2004). Each brain imaging method has four distinct characteristics: spatial resolution, temporal resolution, cortical coverage, and system complexity including cost. For example, invasive methods such as electrocorticography and intracortical neuron recording show high spatial and temporal resolution, but only narrow cortical areas can be measured. In addition, the invasive methods are accompanied by surgery, which limits their application at a high cost. On the other hand, functional magnetic resonance imaging can measure a larger cortical coverage with high spatial resolution, but this method also has the disadvantages of low temporal resolution and high costs. Among the various brain imaging methods, the EEG method has been most well-studied because of its advantages such as low prices, convenience, mobility, large cortical coverage, and high temporal resolution compared to other methods (Amiri, Rabbi, Azinfar, Fazel-Rezai, & Asadpour, 2013).

1.2.2. SMR-based BCI-controlled FES Systems

One of the most studied of many BCI systems is SMR-based BCIs which utilize MIs. Beisteiner et al. (1995) defined the MI as *"an imagined rehearsal of a motor act without any overt movement"* (p. 183), and SMRs induced by MIs are characterized by (de)synchronization in the alpha and beta frequency bands over the bilateral, contralateral, and ipsilateral motor cortex areas (Müller et al., 2003; Neuper, Wörtz, & Pfurtscheller, 2006; Pfurtscheller, 1977; Pfurtscheller & Aranibar, 1979). Pfurtscheller (1977) first introduced the terminology Event-Related Desynchronization (ERD) to describe event-related attenuation in the EEG signal. He then added the term Event-Related Synchronization (ERS) to explain event-related enhancement (Pfurtscheller, 1992). These SMR features, ERD and ERS, have been widely employed to decode different MIs, such as left or right-hand motor intention (McFarland, Miner, Vaughan, & Wolpaw, 2000; Pfurtscheller & Neuper, 2001; Pfurtscheller & Neuper, 1997).

Combining SMR-based BCIs and FES systems to help severely or completely paralyzed patients is a new approach. This combination could not only restore motor functions (Pfurtscheller et al., 2003), but it also has the potential to facilitate neuroplasticity by performing MIs (McGie et al., 2015). Furthermore, BCI-controlled FES systems can provide the result of the imagined motion through proprioceptive sensory feedback (Hara, 2008). For instance, Daly et al. (2009) utilized the brain signals to trigger FES during index finger movement training, and the participant showed the recovery of the volitional isolated index finger movements. In addition, Takahashi et al. (2012) applied an SMR-based BCI-controlled FES system to perform dorsiflexion of the paralyzed ankle in a patient with stroke. The authors

reported a promising result in that both the amplitude of EMG in the affected tibialis anterior muscle and the range of movement at the ankle joint significantly increased with the SMR-based BCI-controlled FES system in comparison with FES alone. McGie et al. (2015) compared five different interventions, such as (1) BCI-controlled FES, (2) EMG-controlled FES, (3) conventional push-button-controlled FES, (4) voluntary grasping, and (5) BCI-guided voluntary grasping with ten healthy participants to investigate the effects on neuroplasticity. The authors assessed changes in motor-evoked potentials induced by transcranial magnetic stimulation before and after each training session, and the results showed higher upregulated potentials after applying BCI-FES and EMG-FES methods than other conventional therapies. They argued these results supported the hypothesis that BCI-FES and EMG-FES methods could induce greater changes in terms of neuroplasticity than other therapies. More support for the use of SMRs induced by MIs as promising interventions to improve motor function rehabilitation in stroke patients was found in Sharma and colleagues' systematic review (2006). There were also many studies showing positive outcomes in using SMR-based BCIs for rehabilitation of patients with severe motor impairments (Daly & Wolpaw, 2008; Stevens & Stoykov, 2003; de Vries & Mulder, 2007).

1.2.3. Limitations of Current SMR-based BCIs for FES Studies

Although SMR-based BCI-controlled FES systems seem promising for rehabilitation of patients with stroke and TBI, there are three main limitations in recent research studies.

Firstly, most of the current research studies have not clearly described the procedures of MI training in the BCI systems. Brain signals vary not only from person to person, but within the same person due to the non-stationarity of brain signals (Krusienski et al., 2011; Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007). Thus, machine learning techniques with a set of training procedures have been adopted to improve BCI performance (Vidaurre & Blankertz, 2010). Although there are many studies that have strived to reduce the training period (Guger, Edlinger, Harkam, Niedermayer, & Pfurtscheller, 2003; Pfurtscheller & Neuper, 2001), SMR-based BCI systems still require relatively longer training than other BCI technologies, such as steady-state evoked potential or Event Related Potential (ERP). In addition, since MI tasks to evoke SMR are mental imaginations that do not involve physical feedback, experimenters or physical therapists cannot know whether the patient is properly performing the MI tasks. To address these issues, users should to be provided with clear MI procedures for easy and efficient training. However, only few research studies focus on these issues (Blankertz, Dornhege, Krauledat, Müller, & Curio, 2007; Gatti et al., 2013; Schuster et al., 2011).

Secondly, SMR-based BCIs using EEG signals currently have limited ability to classify two different MIs in a single hand, such as grasping and opening, due to the low accuracy of the current classification algorithms. Some SMR-based BCI studies have classified two different motor functions in a single hand by applying contralateral MIs, such as a right hand MI for grasping and a left foot MI for extension. However, this approach may be not able to

facilitate neuroplasticity completely due to unnatural control. It is also difficult to distinguish between voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs, because both conditions elicit similar brain activity (Müller et al., 2003). This result implies that it is difficult to stop or keep electrical stimulation by using SMR features because brain signals contain voluntary MI-evoked SMRs, or passive motion-evoked SMRs mixed with strong electrical artifacts.

Lastly, due to the lack of functionality of off-the-shelf FES units, it is difficult to produce natural motor functions. Many commercially available FES systems have only two or four electrodes to deliver electrical stimulation, so the application of electrical stimulation to multiple muscles and nerves for natural hand and wrist movements is limited. Beyond this, only a few FES systems support real-time computer control that is essential for synchronizing MI-evoked brain signals and FES-driven physical feedback. Although some medical and research purpose-built FES systems support multi-channel electrodes and real-time control, these systems are either expensive or not commercially available in the United State.

1.3. The Objectives of Research

The objectives of this study were to address the limitations of current research by:

1) Developing a customized FES platform with real-time computer-controlled functionality to realize natural hand and wrist motions via brain signals.
2) Proposing a systematic parameter determination procedure to enhance user satisfaction, as well as providing adequate initial FES electrode coordinates.
3) Proposing a novel SMR-based BCI system with visual guidelines for MI training not only to classify a 2-class MI task between grasping and opening in a single hand, but also to decode voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs.
4) Validating the proposed SMR-based BCI-controlled FES system by performing goal-oriented tasks with stroke and TBI patients.

The following chapter includes a survey of current FES systems and literature reviews of SMR-based BCI-controlled FES to identify essential features of FES units, as well as to clarify current research limitations.

2. LITERATURE REVIEW AND SURVEY

This chapter consists of a survey and literature review. First, the anatomy of skeletal muscles for FES, as well as FES principles and guidelines were surveyed. Afterward, the FES systems used in current SMR-based BCI research studies were reviewed to identify essential elements necessary to develop a custom FES system, as well as to clarify current limitations of FES studies. In addition, SMR-based BCI research studies were reviewed to identify important features to consider in BCI systems, such as MI training methods, EEG electrode placement, and signal processing procedures including classification algorithms. This review also clarified current limitations of SMR-based BCI studies. Finally, the hypotheses were set on the basis of the survey and literature reviews according to the objectives of this study.

2.1. FES System Survey

When using FES systems, many factors should be taken into account such as (1) guidelines including precautions, contraindications, and skin preparations; (2) the anatomy of skeletal muscles according to different hand and wrist motions, and (3) important features including FES electrode placement and parameters in FES operation. The following sections briefly introduced FES principles, and then summarized FES guidelines, principal muscles for grasping and opening motions, and essential features in FES operation.

2.1.1. FES Principles

Neuromuscular electrical stimulation, also known as electrical muscle stimulation or electromyostimulation, uses electrical stimulation to elicit muscle contraction (Chae et al., 2008). FES refers to the practical utilization of electrical stimulation to support or restore motor functions for patients with motor disorders, and it focuses on goal-oriented tasks such as walking, reaching, and grasping (Peckham & Knutson, 2005). Peckham and Knutson distinguished between therapeutic electrical stimulation and FES, with the former intended *"to improve tissue health or voluntary function by inducing physiological changes that remain after the stimulation is used,"* while FES intervention is used *"to enable function by replacing or assisting a person's voluntary ability"* (2005, p.328). Quandt and Hummel (2014) also distinguished between therapeutic electrical stimulation and FES, and the authors defined the role of the former as inducing physiological changes by promoting brain plasticity and improving spontaneous motor functions, and that of the latter as supplementing lost motor functions by stimulating muscles in a coordinated manner. However, these terminologies are used interchangeably by people in different fields, such as physical therapists, neuroscientists, and biomedical engineers. In this study, the definition of FES was limited to stimulating muscles to restore motor functions.

As the FES system can deliver electrical stimulation directly to the neuromuscular system for muscle contraction, it can replace the lost muscle functions in patients with disabilities (Peckham & Knutson, 2005). Once FES is applied to motor nerves, action potentials are generated and propagated along the axon to the target muscle (Popovic et al.,

2001; Sujith, 2008). The stimulated muscle then contracts when the action potentials are propagated to the muscle (Popovic, Curt, Keller, & Dietz, 2001).

Electrical stimulation can be delivered via surface (transcutaneous), percutaneous, or implanted electrodes (Khamisha, 2011). Although each electrode type has its own advantages and disadvantages as shown in Table 2.1, surface electrodes are widely used because they are cheap, easy to use, and readily available on the market, unlike implanted electrodes that require surgical placement (Doucet, Lam, & Griffins, 2012; Peckham & Knutson, 2005; Popovic et al., 2001).

Table 2.1. Comparisons of different FES electrode types
(Retrieved from Peckham and Knutson (2005), Doucet et al. (2012) and Popovic et al. (2001))

	Surface	**Percutaneous and Implanted**
Electrode Position	- Placed on the skin	- Inserted through the skin into the nerves or muscles
Advantage	- Flexibility to support various treatments - No surgical intervention - Easy to remove - Easy to apply	- Higher muscular selectivity - Less setup time after implantation - Minimizing discomfort
Disadvantage	- Necessity of assistance to place the system - Less convenient in the ADL	- Surgical intervention - Higher cost - Skin irritation - Breaking or dislodging of the electrode

2.1.2. Precautions and Contraindications of FES

When applying FES to users, researchers should check precautions and contraindications for patients' safety (Jones & Johnson, 2009; Reed, 1997; Rennie, 2010). Cameron (2012) distinguished contraindications and precautions as "*Contraindications are conditions under which a particular treatment should not be applied, and precautions are conditions under which a particular form of treatment should be applied with special care or limitations*" (p. 9). Reed (1997) defined four contraindications and nine precautions for electrotherapy, and Jones and Johnson (2009) and Rennie (2010) also mentioned some contraindications and precautions. Table 2.2 summarizes the precautions and contraindications to electrotherapy in the literature review. Based on the summary, an FES safety screening questionnaire was completed (See in Appendix A). These questions should be asked to the participant before treatments or experiments and exclude participants with symptoms listed on the questionnaire.

Table 2.2. Precautions and contraindications for electrotherapy

Controversy includes symptoms inconsistently classified.
(Retrieved from Reed (1997), Jones and Johnson (2009), and Rennie (2010))

Contraindications	Controversy	Precautions
- Unstable cardiac conditions	- Epilepsy	- Decreased sensation
- Implanted devices	- Skin disease	- Dysesthesia
(e.g. pacemakers)	- Hyper/hypotension	- Impaired circulation
- Pregnancy	- Impaired cognition	- Over the thorax
- Acute danger of Hemorrhage	- Impaired communication	- Over phrenic nerve
- Acute danger of Thromboembolism	- Malignancy	
- Tuberculosis	- Over the anterior neck	
- Over the eyes		
- Over head		

2.1.3. Principal Muscles for Hand and Wrist Motions

In this section, principal muscles to place FES electrodes were investigated according to each motion. For example, to generate a grasping motion that is essential for improving ADLs (Popovic, Thrasher, Zivanovic, Takaki, & Hajek, 2005), first, the wrist and thumb should be in extension with half-flexion of the four fingers before reaching an object, and the wrist and fingers should be in flexion when the object is close enough to be touched (Clarkson, 2000; Standring et al., 2008). These consecutive movements require precise coordination of extensor and flexor muscles of the fingers and wrist.

The compartment of the flexor muscles on the forearm consists of superficial flexor muscles and deep flexor muscles (Standring et al., 2008). Figure 2.1 shows the anatomy of the anterior forearm muscles. Two colored circles, a blue solid circle and a red dotted circle, indicate flexor muscles of the wrist and fingers, respectively. The superficial flexor muscles consist of Pronator Teres (PT), Flexor Carpi Radialis (FCR), Palmaris Longus (PL), Flexor Digitorum Superficialis (FDS), and Flexor Carpi Ulnaris (FCU), while the deep flexor muscles are composed of Flexor Digitorum Profundus (FDP), Flexor Pollicis Longus (FPL) and Pronator Quadratus (PQ). Among them, FCR, PL, and FCU are the muscles on which the FES electrodes should be placed because they are responsible for the wrist flexion. FPL is the muscle for flexion of the thumb, while FDS and FDP are for the flexion of the middle and distal phalanges of the four fingers, respectively.

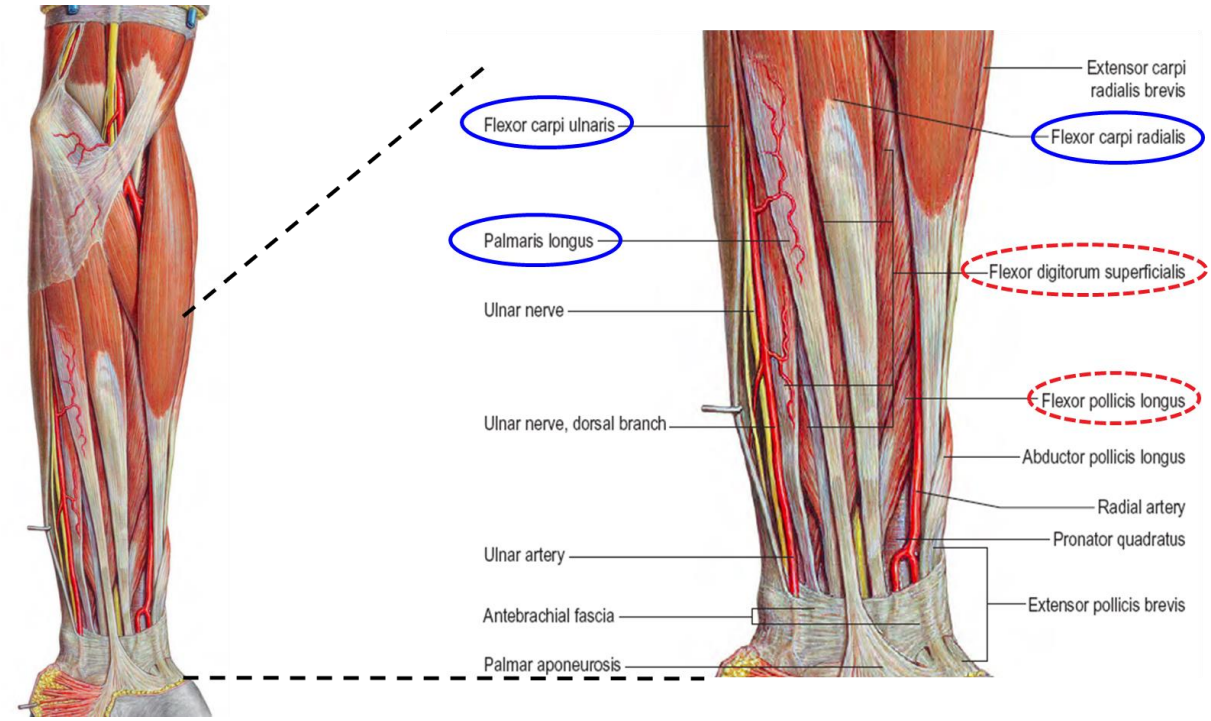


Figure 2.1. Superficial flexor muscles of the left forearm.

Blue solid circles indicate the flexor muscles of the wrist, and red dotted circles refer the flexor muscles of the fingers. Flexor digitorum profundus is superimposed on flexor pollicis longus. (Modified from Gray's Anatomy. 40th Ed. p. 846, Fig. 49.12 and Fig. 49.13)

Similarly, the compartment of the extensor muscles on the forearm consists of superficial extensor muscles and deep extensor muscles (Standring et al., 2008). Figure 2.2 shows the muscle anatomy of the posterior forearm, and a blue solid circle and a red dotted circle indicate extensor muscles of the wrist and fingers, respectively. Superficial extensor muscles are composed of brachioradialis, Extensor Carpi Radialis Longus (ECRL), Extensor Carpi Radialis Brevis (ECRB), Extensor Digitorum Communis (EDC), extensor digiti minimi, Extensor Carpi Ulnaris (ECU), and anconeus. Deep extensor muscles consist of the abductor pollicis longus, Extensor Pollicis Longus (EPL), Extensor Pollicis Brevis (EPB), extensor indicis, and supinator. Among them, ECRL, ECRB, and ECU carry out wrist extension, so

FES electrodes should be placed on those muscles. For fingers, EDC is the muscle for the extension of the four fingers, and EPL and EPB are the muscles for thumb extension.

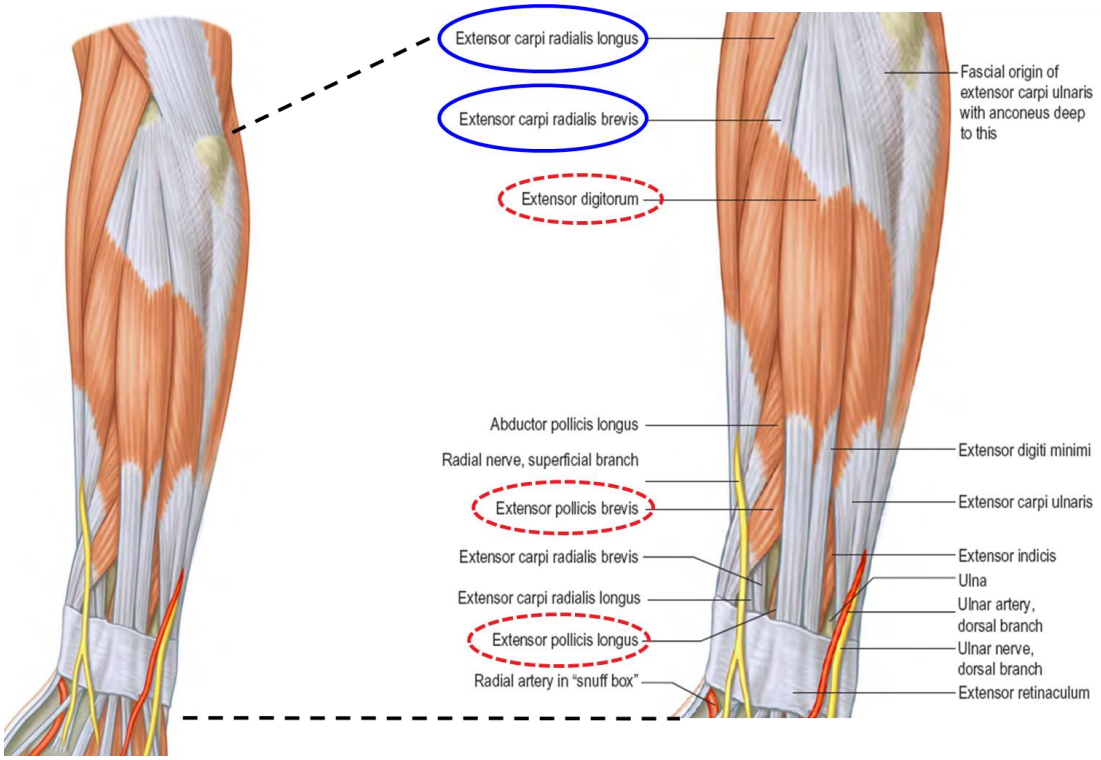


Figure 2.2. Superficial extensor muscles of the left forearm.

Blue solid circles indicate the extensor muscles of the wrist, while red dotted circles show the extensor muscles of the fingers. (Modified from Gray's Anatomy. 40th Ed. p. 848, Fig. 49.14)

Table 2.3 organizes the flexor and extensor muscles on the forearm for controlling wrist and fingers, as well as the innervating nerves. This table also includes motion generated by each muscle. Similar motions can be produced by applying electrical stimulation to the corresponding muscles, which are used in Study 1 to identify proper electrode placement.

Table 2.3. Flexor and Extensor muscles on the forearm

(Retrieved from Gray's Anatomy. 40th Ed. p. 784, Fig. 45.1)

Movement		Muscle	Abbreviation	Nerve
Flexor	**Wrist**	Flexor carpi radialis	FCR	Median
		Palmaris longus	PL	Median
		Flexor carpi ulnaris	FCU	Ulnar
	Fingers	Flexor digitorum profundus	FDP	Anterior interosseous & ulnar
	Thumb	Flexor pollicis longus	FPL	Anterior interosseous
Extensor	**Wrist**	Extensor carpi radialis longus	ECRL	Radial
		Extensor carpi radialis brevis	ECRB	Posterior interosseous
		Extensor carpi ulnaris	ECU	Posterior interosseous
	Fingers	Extensor digitorum	EDC	Posterior interosseous
	Thumb	Extensor pollicis longus	EPL	Posterior interosseous
		Extensor pollicis brevis	EPB	Posterior interosseous

2.1.4. Features in FES Operation

A few FES systems are commercially available and each system has different capabilities, such as the number of FES electrodes, current amplitude, pulse rate, pulse width, the stimulation waveform, and application of ramp time. Furthermore, various FES electrode sizes and shapes are readily available in the market.

Choosing the right number of FES electrodes and their placement is important to generate natural hand and wrist movements. For example, at least two pairs of electrical stimulation channels are required to reproduce wrist flexion and extension (Lawrence, 2009). A pair of FES electrodes, including a cathode electrode (negative, black lead) placed on wrist extensors such as ECRL, ECRB, and ECU and an anode electrode (positive, red lead) placed near the lateral epicondyle, are needed to achieve wrist extension. Another pair of FES electrodes is also required for wrist flexion, and a cathode electrode should be located on wrist flexors such as FCR, PL, and FCU, while an anode electrode should be placed near the medial epicondyle. Similarly, finger flexion and extension also require a pair of electrodes, respectively. Since the grasping force is generated by the pressure between the thumb and the other fingers, the extension and flexion of the thumb also play an important role in grasping (Bertelli, Tacca, Ghizoni, Kechele, & Santos, 2010). Therefore, four to six pairs of FES electrodes are required to perform natural hand movements such as grasping and opening.

If the FES electrodes are not in the adequate position, it can cause not only unwanted motion (Lawrence, 2009), but also induce muscle pain and discomfort to the user (Lyons, Leane, Clarke-Moloney, O'Brien, & Grace, 2004). However, Lawrence (2009) found that anode electrode placement had no significant effect on muscle contraction unless the distance

between anode and cathode electrode was greater than 2 cm. Figure 2.3 illustrates an example of FES electrode placement for wrist extension and flexion of the right forearm.

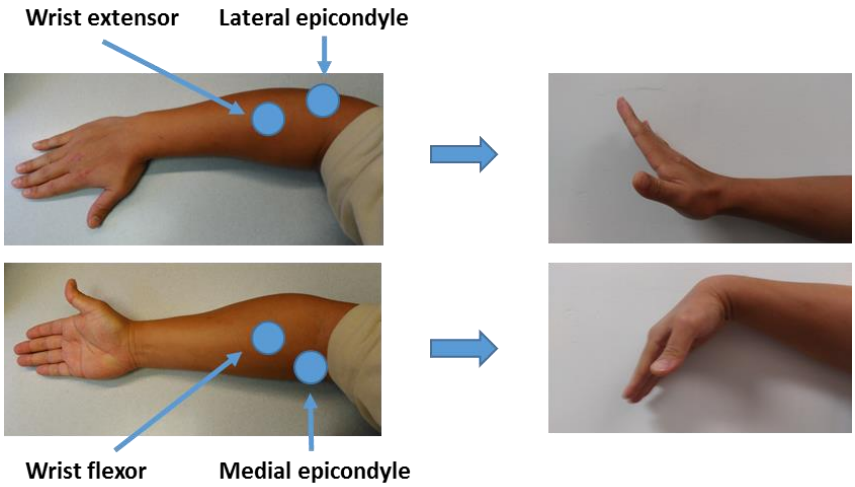


Figure 2.3. Electrode placement on the right forearm for wrist extension and flexion

Another important feature of electrical stimulation is pulse rate, also called the stimulation frequency. To avoid muscle twitches and to achieve functional and sustained muscle contraction, pulse rate should be set above 20 Hz (Popovic et al., 2001). Benton et al. (1991) argued that higher pulse rate could produce stronger muscle contraction, but also could cause faster muscle fatigue during continuous stimulation. Matsunaga and colleagues (1999), however, reported the opposite result for intermittent low frequency (20 Hz) and intermittent high frequency stimulation (100 Hz). The authors found that intermittent stimulation of 4 seconds caused less muscle fatigue at the higher frequency than at the lower frequency. These two conflicting results are useful in determining pulse rate depending on the duration of muscle contraction.

The strength of muscle contraction can be controlled by current amplitude and pulse width (Sabut et al., 2011; Thrasher et al., 2008). Pulse width, also known as pulse duration, is the stimulus time per cycle, and current amplitude is the intensity of electrical stimulus delivered by each pulse. Figure 2.4 shows examples of different current amplitudes and pulse widths. Figure 2.4 (a) indicates a 25% duty cycle (stimulation is delivered during 25% of the cycle time), while (b) shows a 50% duty cycle within the same cycle time. Figure 2.4 (c) shows a 50% duty cycle waveform with twice the amplitude shown in Figure 2.4 (a) and (b).

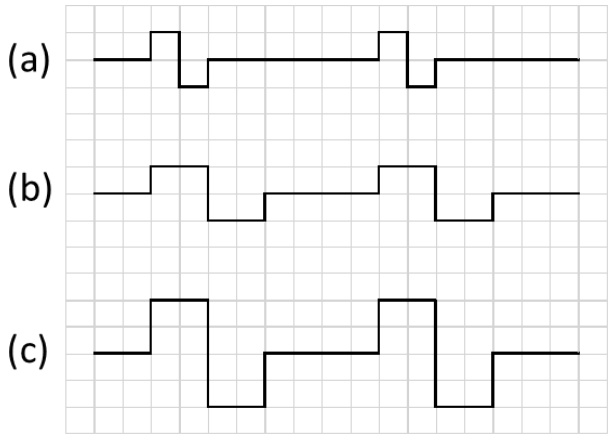


Figure 2.4. Examples of different current amplitude and pulse width.
(a) 25% duty cycle, (b) 50% duty cycle within the same cycle, and (c) twice amplitude than others.

Crago et al. (1980) found that the strength of muscle contraction has a nonlinear relationship with current amplitude or pulse width, and that the shape of the nonlinearity is affected by the location of the electrode on muscle and muscle length. However, there are only a few models that estimate the appropriate current amplitude and pulse width needed to maximize user satisfaction with respect to the length and mass of the muscle on which electrodes are placed (Lawrence, 2009; Lyons et al., 2004).

The shape of electrical stimulus waveforms is also a feature to consider. The stimulus waveforms can be classified as monophasic or biphasic. A monophasic waveform has a single phase with a unidirectional pulse having one positive or negative phase, while a biphasic waveform has two phases with both positive and negative phases, as shown in Figure 2.5 (Martínez-Rodríguez, Bello, Fraiz, & Martinez-Bustelo, 2013). Most FES systems employ biphasic electrical stimulation because a constant polarity from monophasic stimulus can cause skin burns, muscle fatigue, and tissue damage (Martínez-Rodríguez et al., 2013; Popovic et al., 2001). The biphasic waveform can have three shapes: symmetric, balanced asymmetric, and unbalanced asymmetric. Figure 2.5 illustrates four different monophasic and biphasic waveforms. Between symmetrical and asymmetrical electrical waveforms, many studies suggest the asymmetrical waveform leads to more effective muscle control and less muscle fatigue than the symmetrical waveform (Keller, Ellis, & Dewald, 2005; Lawrence, 2009; Ragnarsson, 2008).

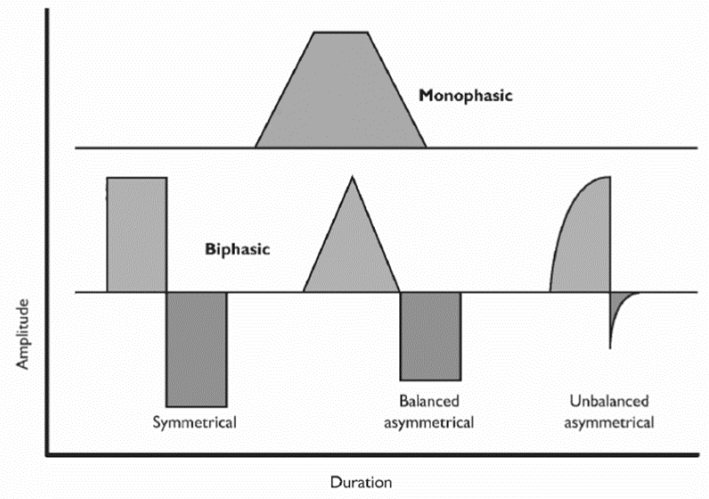


Figure 2.5. Monophasic and biphasic waveforms

(Retrieved from Figure 11.7 in physical agents theory and practice (Behrens & Beinert, 2014))

Ramp time is also an important function to enhance user's comfort. Ramp time, which typically lasts for 1 to 3 seconds, can be applied to current amplitude or pulse rate, and it indicates the duration from the beginning of stimulus to the desired current amplitude or pulse rate (Baker, Wederich, McNeal, Newsam, & Waters, 1993). Figure 2.6 shows an example of ramping in current amplitude.

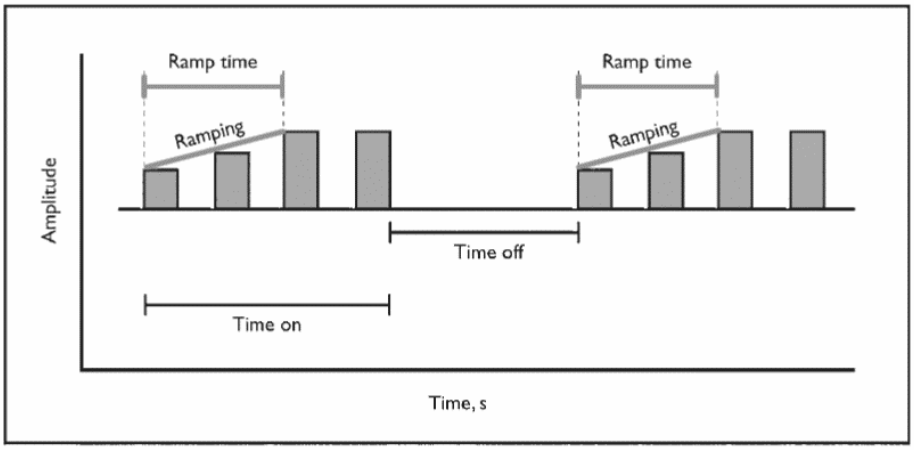


Figure 2.6. Ramp time for current amplitude
(Retrieved from Figure 11.21 in Physical agents theory and practice (Behrens & Beinert, 2014))

The size and shape of the electrode pads also affect muscle contraction and user satisfaction. When the electrical stimulus is distributed under the electrode surface area, the current density and surface area have an inverse relationship. This means that small electrodes can deliver high current density on a small area, and vice versa (Patterson & Lockwood, 1991). Generally, large electrode pads can deliver the same current amplitude while reducing muscle pain and discomfort compared to small electrode pads (Patterson & Lockwood, 1991). However, the size of the electrode pads should reflect the size of the target muscle (Keller & Kuhn, 2008). For example, a cathode electrode should be placed on the abductor pollicis brevis

muscle to generate thumb abduction, and if the cathode electrode is too large for the stimulation site, then electrical stimulation also stimulates adjacent unrelated muscles and nerves, resulting in undesirable motion. Table 2.4 lists various sizes and shapes of electrode pads using a standard 2 mm diameter lead wire with a pin connector. Figure 2.7 shows the three selected electrode pads which are readily available on the market. These electrodes contain self-adhesive hydrogel on the pad, making it easier to attach electrodes on the skin and to improve contact and electrical conductivity between the skin and electrodes (Lawrence, 2009).

Table 2.4. Various sizes and shapes of FES electrode pads

These electrodes are available on Axelgaard.com (Axelgaard Manufacturing Co., Ltd., Fallbrook, CA) and TensUnits.com (TensUnits.com, Largo, FL). All units are inches.

Oval	Round	Square	Rectangle
1.5 X 2.5	1	2 X 2	1.3 X 2.1
2 X 4	1.25	1.5 X 1.5	1.5 X 3
3 X 5	2		2 X 3.5
	2.75		2 X 5
	3		3 X 4
	4		2 X 4 (Dual Lead)

(a) **(b)** **(c)**

Figure 2.7. Three different types of FES electrodes with a 2 mm pin connector

(a) 2" X 2" square (b) 2" round (c) 2" X 3.5" rectagle electrode pads (All units are inches)

(Retrieved from TensUnits.com (TensUnits.com, Largo, FL))

2.1.5. Summary

In this section, the survey of FES systems confirms the precautions and contraindications before applying FES (Jones & Johnson, 2009; Reed, 1997; Rennie, 2010). The FES safety screening questionnaire for FES experiments is available in Appendix A, which summarized precautions and contraindications from the survey. The principal muscles for extension and flexion of the hand and wrist are also identified. Finally, the important features in building a custom FES platform are identified, such as the number of FES electrodes, FES electrode placement, pulse rate, pulse width, current amplitude, stimulation waveforms, ramp time, and FES electrode pad types.

The summary of the survey is as follows:

- Surface FES electrodes are widely used because they are cheap, easy to use, and readily available on the market (Doucet et al., 2012; Peckham & Knutson, 2005; Popovic et al., 2001)
- Before applying FES to participants, the investigator should check precautions and contraindications (Jones & Johnson, 2009; Reed, 1997; Rennie, 2010).
- The precise coordination of flexor and extensor muscles on which FES electrodes are placed is necessary for natural hand and wrist motions (Clarkson, 2000; Standring et al., 2008).
- Determination of a suitable number of electrodes and cathode electrode placement are essential to generate natural hand and wrist motions (Lawrence, 2009).

- To avoid muscle twitches and to achieve functional, continuous muscle contraction, pulse rate should be set above 20 Hz (Popovic et al., 2001).
- The strength of muscle contraction can be controlled by current amplitude and pulse width (Sabut et al., 2011; Thrasher et al., 2008).
- Asymmetric biphasic waveforms are more effective for muscle contraction, and induce less muscle fatigue than symmetrical stimulation (Keller et al., 2005; Lawrence, 2009; Ragnarsson, 2008).
- Ramp time is also an important function that could improve the user's comfort (Baker et al., 1993).
- The size and shape of the electrode pads also affect muscle contraction, and large electrode pads are generally preferred for reducing muscle pain and discomfort (Patterson & Lockwood, 1991).

2.2. Review on FES Systems for SMR-based BCI

In this section, the FES systems used in SMR-based BCI studies were systematically reviewed in order to determine the scope of application of the important features defined in the previous survey needed to build a customized FES system. In the literature review, FES electrode placement and parameters used in previous research studies were summarized. Afterward, the limitations of current studies were outlined.

2.2.1. Systematic Review Procedure

For the systematical review, the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) method was applied (Liberati et al., 2009; Moher et al., 2015; Moher, Liberati, Tetzlaff, Altman, & Grp, 2009). Liberati et al. (2009) defined the aim of PRISMA as *"to help ensure the clarity and transparency of reporting of systematic reviews, and recent data indicate that this reporting guidance is much needed"* (p. w-87). When using the PRISMA method, the eligibility criteria included journal articles written in English from 2003 to February 2016, as the first peer-reviewed journal article related to BCI-controlled FES systems did not appear until 2003 (Pfurtscheller et al., 2003). The search engines used in this review were Web of Science, PubMed, and Engineering Village, because these search engines cover both engineering and medical publications (Powers, Bieliaieva, Wu, & Nam, 2015). The keywords used in the search engines were a combination of either "brain computer interface" or "brain machine interface" and either "functional electrical stimulation" or "neuromuscular electrical stimulation". After searching for keywords, 94, 51, and 42 articles were searched by

each search engine, respectively, and 97 articles were left after removing duplicate articles. Afterward, the remaining articles were screened out based on the titles and abstracts related to BCI-controlled FES systems only. Prescreened 53 articles were checked for eligibility based on full-text screening with some exclusion criteria, such as (1) articles for non-journal, book chapter, or review papers; (2) experiments for non-human primates; (3) invasive brain imaging methods and implanted electrical stimulation systems; (4) articles for neuroscience studies that did not focus on motor function restoration, and (5) studies not related to hand and wrist control. After eligibility screening, only 18 studies remained for the review of the FES systems. Figure 2.8 shows the screening procedures and results.

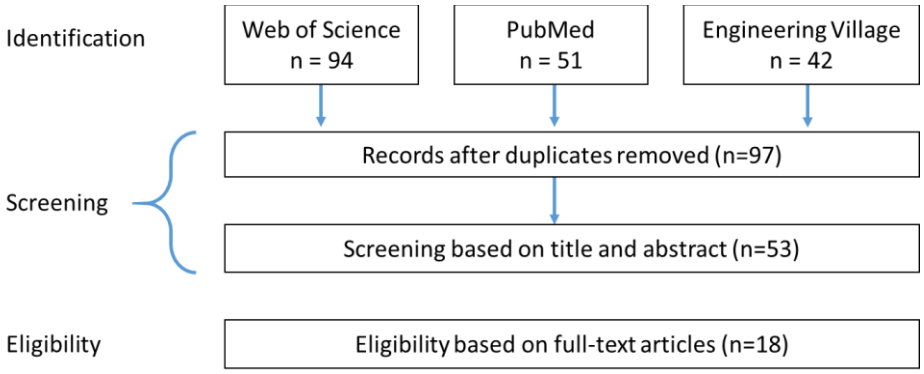


Figure 2.8. PRISMA flow diagram for FES systems used in BCI studies

2.2.2. FES Systems in Current Research

To determine the extent of application of critical features that should be applied when building a customized FES system, the FES systems used in 18 selected papers were analyzed. As a result, 9 different FES systems were discovered, three of which did not support real-time computer control, and were customized to meet the authors' specific research objectives. Of

the other six FES systems, RehaStim and Compex Motion were not commercially available in the United State in 2016, and MEB-2200 was discontinued by the manufacturer. Universal External Control Unit and MOTIONTIM 8 were also not readily available in the US market, while the design of NESS H200 was not suitable for this study.

The number of electrode channels supported by these FES units are between 2 to 8 channels, except for Universal External Control Unit, which supports up to 32 channels. Pulse rate of these devices are up to 150 Hz, but most can cover from 1 to 99 Hz. The range of pulse width is between 10 and 500 μs except for Compex Motion, which supports up to 16,000 μs, and the range of current amplitude is up to 150 mA. Table 2.5 summarizes the names and parameters of each FES system used in these studies.

Table 2.5. FES systems used in the previous studies

FES System	# of Channels	Pulse Rate (Hz)	Pulse Width (μs)	Current Amplitude (mA)	Used Research Studies
Universal External Control Unit	32	1 ~ 80	~ 255	0 ~ 60	(Daly et al., 2009)
RehaStim	8	1 ~ 140	20 ~ 500	0 ~ 130	(Elnady et al., 2015; Reynolds, Osuagwu, & Vuckovic, 2015; Vuckovic, Wallace, & Allan, 2015)
Compex Motion	4	1 ~ 100	75 ~ 16,000	0 ~ 125	(McGie et al., 2015; Tan et al., 2011)
MEB-2200	2	-	-	-	(Mukaino et al., 2014)
MOTIONSTIM 8	8	1 ~ 99	10 ~ 500	0 ~ 125	(Pfurtscheller et al., 2003, 2005; Rohm, Muller-Putz, Kreilinger, von Ascheberg, & Rupp, 2010; Rohm et al., 2013)
NESS H200	5	18 or 36	10 ~ 500	0 ~ 150	(Roset, Gant, Prasad, & Sanchez, 2014)
Microstim (customized)	2	1 ~ 99	~ 250	1 ~ 99	(Kim, Kim, & Lee, 2016)
EMPI 300PV (customized)	2	1 ~ 99	10 ~ 500	0 ~ 100	(Looned, Webb, Xiao, & Menon, 2014)
LG-7500 (customized)	2	1 ~ 150	30 ~ 260	0 ~ 90	(Young et al., 2014, 2015)

2.2.3. FES Electrode Placement and Parameters in Current Research

In this section, FES electrode placement and parameters used in previous studies were reviewed. FES electrodes should be placed on the correct position according to the target motions in order to avoid unnatural and uncomfortable movements (Lawrence, 2009; Lyons et al., 2004). Therefore, precise electrode placement is important for generating natural hand-wrist motions. However, the proper electrode positions depend on target hand motions as mentioned in section 2.1.3. Furthermore, appropriate electrode placement also varies from person to person due to anatomical differences in length and mass of the forearm (Gordon, Churchill, Clauser, Bradtmiller, & McConville, 1989). Despite of the importance, two of 18 articles did not mention information about electrode placement, and the other articles also ambiguously described the name of muscle without referring the exact location as shown in Table 2.6, which summarizes the authors' comments from the literature review. For example, Young, et al. (2014) mentioned that a pair of electrodes were placed on the extensor carpi radialis longus/brevis and on the portion of the extensor digitorum to generate the extension of wrist and fingers. The green circles shown in Figure 2.9 indicate the estimated locations from what the authors mentioned, but the area of locations are too large to specify the exact positions.

Table 2.6. Comments for electrode placement in the previous studies

Article	Electrode Placement
(Daly et al., 2009)	Placed over the indicis proprius muscle and the portion of the extensor digitorum communis muscle serving the index finger
(Elnady et al., 2015)	Attached to the stroke affected extensor digitorum
(Tan et al., 2011)	One electrode was placed proximally over the forearm below the elbow, and the other was placed distally on the forearm (positioned for optimally balanced joint movement).
(Kim et al., 2016)	FES was triggered and stimulated wrist extensor muscles of the affected upper extremity
(Liu et al., 2014)	FES is triggered and delivered to patients' extensor carpus radialis muscles, which causes real movement of their hands or arms
(Looned et al., 2014)	Hand opening was achieved by placing two electrodes on the distal and proximal ends of the extensor digitorum muscles of the forearm [35].
(McGie et al., 2015)	Stimulate the following muscles: flexor carpi radialis, flexor digitorum superficialis, and flexor digitorum profundus (FCR/FDS/FDP), abductor pollicis brevis/ flexor pollicis brevis (APB/FPB/OP), and extensor digitorum (for wrist/finger extension).
(Mukaino et al., 2014)	Placed over the muscle belly of the extensor digitorum communis (EDC) on the paralysed side
(Pfurtscheller et al., 2003)	The finger (M. ext. digitorum communis EDC) and thumb (M. ext. pollicis longus EPL) extensors for hand opening, the finger flexors (M. flex. digitorum superficialis FDS, M. flex. digitorum profundus) hand closing, the thumb flexor (M. flex. pollicis longus FPL) for grasping and the wrist extensors (M. ext. carpi radialis longus/brevis ECRL/ECRB) for stabilization of the hand.
(Pfurtscheller et al., 2005)	An opening of the hand (phases 1 and 4, Figure 1) by extension of all fingers joints and the thumb could be achieved by stimulation of the finger extensors (M. extensor digitorum communis) and the thumb extensor muscle (M. extensor pollicis longus) with electrodes on the radial side of the proximal forearm. For the actual grasping (phase 2, Figure 1), we simultaneously stimulated the finger flexors (M. flexor digitorum superficialis, less the M. flexor digitorum profundus) by one pair of electrodes on the ulnar side of the proximal forearm and the intrinsic hand muscles with two further electrodes on the dorsal side of the hand. The
(Reynolds et al., 2015)	Placed on the right hand extensor muscles

(Rohm et al., 2010)	-
(Rohm et al., 2013)	The finger extensors (extensor digitorum communis; electrode pair (EP) 1 in Fig. 1A), the finger flexors (flexor digitorum superficialis, flexor digitorum profundus; EP 2 in Fig. 1B) and the thumb extensor (extensor pollicis longus; EP 3 in Fig. 1A) and flexor (flexor pollicis longus; EP 4 in Fig. 1B) of the right hand were stimulated via four separate pairs of surface electrodes.
(Roset et al., 2014)	Extensor muscles (extensor digitorum communis and extensor pollicis brevis)
(Vuckovic et al., 2015)	The wrist extensor muscles (extensor carpi radialis longus).
(Tam et al., 2011)	Extensor carpi radialis
(Young et al., 2014)	Extensor carpi radialus brevis and extensor digitorum muscles
(Young et al., 2015)	Placed over the indicis proprius muscle and the portion of the extensor digitorum communis muscle serving the index finger

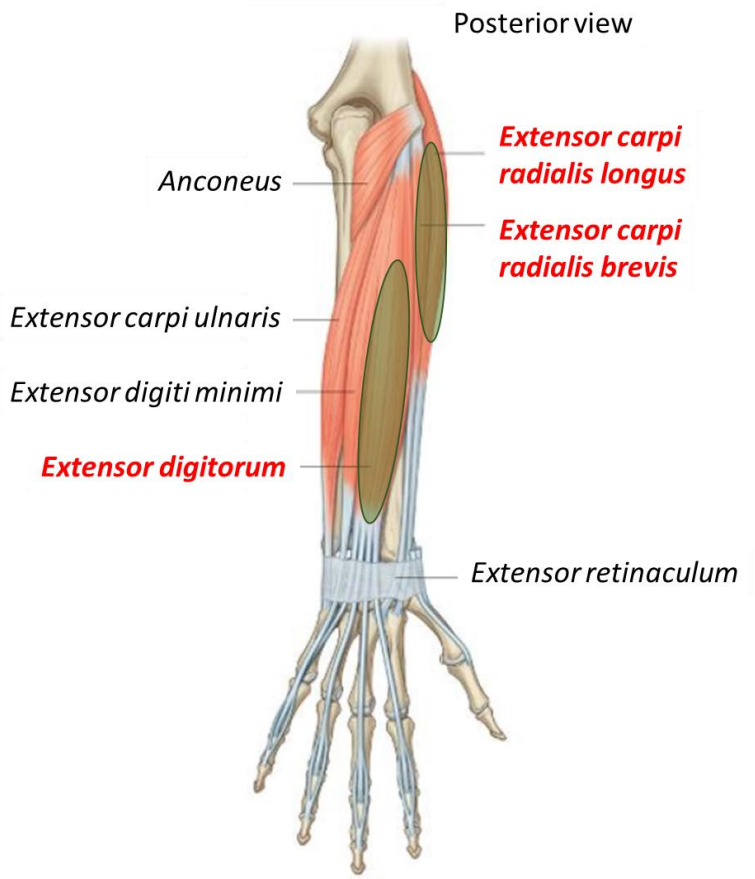


Figure 2.9. Superficial muscles in the posterior forearm.

Green circles indicate the positions to place cathode electrodes for wrist and finger extension. (Retrieved from Gray's Anatomy for Students. 2nd Ed. p. 1055, Fig. 7.88)

In addition, there were only two studies mentioning the size and shape of the electrode pads used, and only five of them specified the number of electrodes utilized. Although Forrester and Petrofsky (2004) disputed the effects of electrode pad size and shape on the tolerance of electrical stimulation, sufficient studies support the size and shape of electrodes as important factors for motor functionality and user comfort (Alon, 1985; Lyons et al., 2004; Patterson & Lockwood, 1991).

As mentioned earlier, FES parameters are also important factors, and pulse rate, current amplitude, and pulse width are the most important to achieve the proper motor function. Most studies used a fixed pulse rate but varied between 16 Hz and 83.3 Hz. The pulse width was also different in each study, and all but one study (McGie et al., 2015) adopted a fixed pulse width between 100-300 μs. Current amplitude was usually set to be sufficient for muscle contraction but not uncomfortable. Vuckovic et al. (2015) clearly stated the use of ramp time to reduce muscle fatigue, but not other research studies. Table 2.7 summarizes detailed information on the parameters utilized, with the exception of three studies that did not report information on FES parameters.

Table 2.7. FES parameters in the previous studies

Article	Pulse Rate (Hz)	Pulse Width (μs)	Current Amplitude
(Daly et al., 2009)	83.3	255	Comfortable amplitude
(Elnady et al., 2015)	35	150	Comfortable amplitude
(Tan et al., 2011)	25	250	Comfortable amplitude
(Kim et al., 2016)	60	150	20 ~ 27 mA
(Liu et al., 2014)	60	150	25 mA
(Looned et al., 2014)	25	200	Comfortable amplitude
(McGie et al., 2015)	40	0 to 250	Comfortable amplitude
(Mukaino et al., 2014)	20	100	15 ~ 20 mA
(Pfurtscheller et al., 2003)	16	300	-
(Pfurtscheller et al., 2005)	18	-	-
(Reynolds et al., 2015)	30	200	10 ~ 17 mA
(Rohm et al., 2010)	-	-	-
(Rohm et al., 2013)	16	-	-
(Roset et al., 2014)	35	300	Amplitude for the maximal contraction * 1.25
(Vuckovic et al., 2015)	30	300	15 mA
(Tam et al., 2011)	40	300	50 ~ 80 mA
(Young et al., 2014)	-	-	-
(Young et al., 2015)	-	-	-

2.2.4. Limitations of Current Research

From the systematic literature review of the FES systems for SMR-based BCI, three main issues have been identified and are described below.

Firstly, most FES units used in the previous research were either not commercially (readily) available in the United States or did not support real-time computer control. Also, some functions, such as ramp time (Doucet et al., 2012), were not clearly specified in the articles and specification sheets provided by manufacturers.

Secondly, most of the surveyed research studies did not precisely define the exact electrode positions but vaguely described the name of the muscles where FES electrodes were placed. Furthermore, there was not clear guidance to help identify the proper electrode location with respect to anthropometric data, such as the length and mass of forearm, which varies for each individual.

Thirdly, there were a few studies that considered the HF/E perspective by applying user-specific pulse rate and pulse width to increase user satisfaction, but other studies arbitrarily selected fixed parameters. Therefore, the range of parameters was very wide. In addition, only a few studies applied proper ramp time for current amplitude and pulse rate to achieve natural hand and wrist movements with minimum muscle pain and discomfort.

The summary of limitations and findings in current research studies is as follows:

- FES units with real-time control are not readily available in the United States. Therefore, a customized FES platform is required.
- A proposed FES platform should support a sufficient number of FES electrode channels (up to 8) and a wide range of FES parameters.
- Most of the studies did not precisely define the exact electrode location. There were no procedures to help identify the proper electrode position with respect to anthropometric data.
- There were only a few studies that considered FES parameter setting procedure for user-specific pulse rate and pulse width to improve user satisfaction by minimizing perceived muscle pain and discomfort.

2.3. Review on SMR-based BCIs for FES

The objectives of this review were; (1) to analyze current FES systems, including electrode placement and parameters, controlled by SMR-based BCIs; (2) to investigate current MI training procedures and guidelines; (3) to select an EEG-channel montage used to decode MI features; (4) to define brain features evoked by MI; (5) to identify proper signal preprocessing methods to extract distinct brain features in terms of temporal and spatial filtering, and (6) to analyze current classification algorithms used for MI decoding. After the literature review, limitations of current research were outlined.

In this section, 18 articles selected in Section 2.2.1 were reused to review previous research studies from SMR-based BCI perspectives including EEG electrode placement, MI training procedures, SMR signal features, feature extraction methods, and classification algorithms. However, the studies selected in the previous section were limited to BCI studies using FES systems and did not fully cover studies on SMR-based BCIs. To address this issue, another systematic review was conducted. This systematic review identified current state-of-the-art technologies and summarized the limitations of current research studies.

2.3.1. Systematic Review Procedure

For the systematic review, the PRISMA method was applied in the same way as in Section 2.2.1. Eligibility criteria included journal review articles written in English from 2012 to 19 June 2016. Search engines used in this review included Web of Science, PubMed, and Engineering Village, as in the previous review. Keywords for the search engines were

combinations of either “brain computer interface” or “brain machine interface”, “motor imagery” or “sensorimotor”, and “review”. After keyword searching, 35, 20, and 24 articles were found from each search engine, respectively, with 47 articles left after duplicates were removed. The remaining articles were then screened out based on the titles and abstracts related to SMR-based BCI studies.

Prescreened articles were checked for eligibility based on full-text screening with some inclusion criteria, such as (1) review articles for SMR-based BCI studies and (2) using EEG brain imaging technology. After eligibility screening, 26 studies including 18 studies from the previous review were selected for a review of SMR-based BCI. Figure 2.10 shows the steps and results of screening.

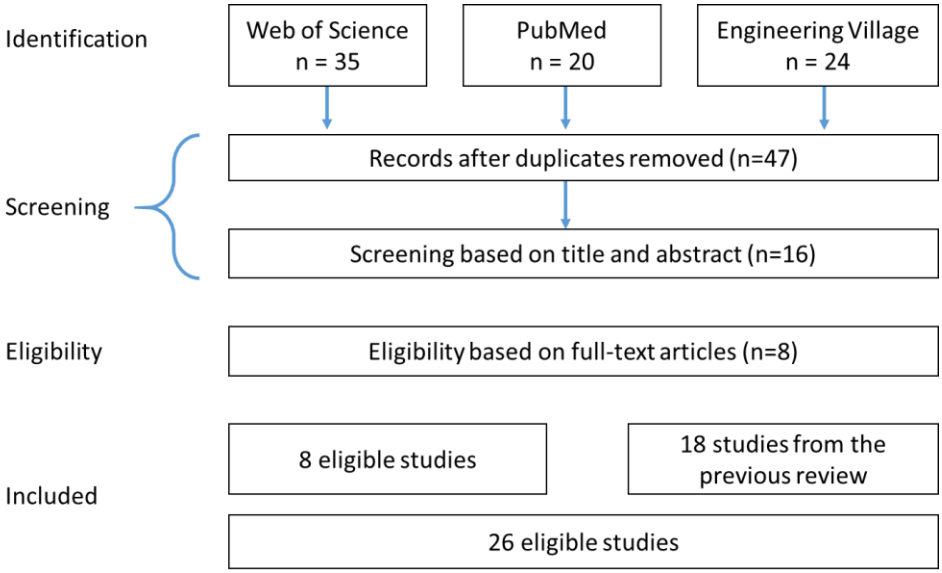


Figure 2.10. PRISMA flow diagram for SMR-based BCI studies

2.3.2. MI Instruction and Tasks in Current Research

A MI task is a mental imagination that does not involve physical movements or physiological feedback (Ang, Guan, Ang, & Cuntai Guan, 2015). This makes SMR-based BCI difficult because (1) experimenters or physical therapists cannot know whether the subject or patient completed MI tasks in the right way; (2) it is somewhat difficult to explain to users how to correctly perform MI tasks, and (3) it could be hard to maintain exactly the same MI tasks during the experiment. To address these issues, clear instructions are required to help both participants and experimenters during training. However, according to the literature review, only two studies (Kim et al., 2016; Looned et al., 2014) provided video clips as visual guidance to help subjects mimic MI tasks, while other researchers verbally explained MI tasks.

MI tasks also varied between studies. Some studies had asked participants to imagine wrist or finger movements (Daly et al., 2009; Tan, Shee, Kong, Guan, & Ang, 2011), while others asked them to imagine waving or reaching motions (Reynolds et al., 2015; Young et al., 2015). Moreover, the frequency of MI tasks varied from study to study. Three studies (Elnady et al., 2015; Mukaino et al., 2014; Reynolds et al., 2015) applied repetitive MI tasks, but other studies applied one-time MIs or did not clearly mention the frequency of MI tasks. Table 2.8 shows authors' instructions for MI tasks mentioned in the surveyed research studies, and what the authors had asked the users to do.

Although not found in the systematic literature review, there were few studies that utilized distinct SMR features induced by different rhythmic MIs. Gu et al. (2009) examined the identifiability of four MI tasks consisting of two MI types (wrist extension and rotation) and two speeds (fast and slow), and the authors reported that the speed variable had greater

classification ability than the MI types. Similarly, Choi et al. (2016) applied slow-continuous MI and fast-transient MI to classify a 2-class MI task in a single hand such as grasping or opening, and the results were promising in terms of classification accuracy.

Table 2.8. Instruction for MI tasks in the previous studies

Article	Instruction
(Daly et al., 2009)	"…attempted finger movement and relax conditions or imagined finger movement and relax conditions."
(Elnady et al., 2015)	"…asked to perform different repetitive imagery tasks according to the stimulus or visual cues…"
(Tan et al., 2011)	"…subjects used hand grasping and wrist flexion/extension movements to elicit motor imagery."
(Kim et al., 2016)	"…were advised to keep focusing on their affected arm/hand action observational tasks." (with video)
(Liu et al., 2014)	"…a bold arrow … instructing patients to imagine left or right."
(Looned et al., 2014)	"…asked to imagine the corresponding motion for each displayed action…"
(McGie et al., 2015)	"…asked to perform motor imagery pertaining to a grasping movement, …"
(Mukaino et al., 2014)	"…asked to attempt finger opening for 3 s at maximal voluntary effort." (at 1 Hz frequency)
(Pfurtscheller et al., 2003)	"…the subject imagines a foot movement, …"
(Pfurtscheller et al., 2005)	"Imaginations of left versus right hand movements were carried out… single-foot motor imageries versus relaxing or hand movement imagination ..."
(Reynolds et al., 2015)	"…instructed to imagine waving with their right hand with a frequency of about 0.5 Hz as soon as they saw the execution cue."
(Rohm et al., 2010)	-
(Rohm et al., 2013)	-
(Roset et al., 2014)	"…instructed the person to either open or close his hand." (with visual cues)
(Vuckovic et al., 2015)	"…instructed to perform kinesthetic motor imagery of activities performed mentally with their left or right hand" (according to the cue)
(Tam et al., 2011)	"…instructed to perform motor imagery of his or her wrist on the affected side."
(Young et al., 2014)	"…taught to use attempted movements of each hand to control the BCI device."
(Young et al., 2015)	"…instructed to use attempted movements of the right or left hand to drive the cursor…"

In terms of imagination tasks, some researchers applied two different conditions, rest and MI, to detecting the presence of SMR, and the user could control a device to initiate or stop the operation by classifying brain signals. In contrast, other researchers utilized two MIs, one hand MI and the other hand (or foot) MI, to classify the directional SMR. In this case, the most common cues that represented the imagination tasks found in the literature review were arrows according to target directions (Liu et al., 2014). However, in these two cases, it was impossible or unnatural to implement hand opening or closing operation through the FES system by classifying SMRs. As shown in Table 2.9, there was only one study that investigated different MI tasks within the same body part, such as imagining opening and closing in a single hand (Roset et al., 2014).

In addition, there was no research that utilized the SMR feature as a criterion to stop FES with the voluntary intention of the user. This is because FES-driven passive-movement-evoked SMRs are similar to voluntary MI-evoked SMRs, and are therefore difficult to classify under electrical stimulation artifacts (Ang et al., 2013; Müller et al., 2003). Due to this phenomenon, most SMR-based BCI systems for controlling FES have applied synchronous methods, also known as cue-based, or added other stimulus modalities, such as visual or tactile stimulation, as a stop trigger (Pfurtscheller, Solis-Escalante, Ortner, Linortner, & Muller-Putz, 2010b).

Table 2.9. MI Classes, analyzed band, and feature extraction methods

Article	MI Classes	Feature Extraction	Classification Methods
(Daly et al., 2009)	Attempted Movement vs. Attempted Relaxation	3 Hz bins from 0 to 30 Hz	Time-averaged power, R-square
(Elnady et al., 2015)	MI vs. Rest	CSP for each electrode	LDA, 10X10 CV
(Tan et al., 2011)	MI vs. Rest	Bandlimited multiple Fourier linear combiner with 1 Hz bin	Compare mu-rhythm
(Kim et al., 2016)	MI or Action Observation vs. Rest	12 ~ 15 Hz (SMR), 16 ~ 20Hz (mid-beta)	(SMR + Middle Beta)/Theta, Threshold
(Liu et al., 2014)	Left MI vs. Right MI	FastICA, Tensor-based nearest feature line distance	SVM
(Looned et al., 2014)	MI vs. Rest or Jaw Clench vs. Rest	7 ~ 13 Hz (mu) and 13 ~ 30 Hz (beta)	LDA
(McGie et al., 2015)	MI vs. Rest	10 ~ 12 Hz and 13 ~ 15 Hz	No clear
(Mukaino et al., 2014)	-	-	-
(Pfurtscheller et al., 2003)	Foot MI vs. Right Hand MI	-	fLDA
(Pfurtscheller et al., 2005)	Both Foot MI vs. Right Hand MI	-	Threshold
(Reynolds et al., 2015)	Left Hand MI vs. Right Hand MI	Select significant band by t-percentile bootstrap	LDA
(Rohm et al., 2010)	Feet MI vs. Hands MI	-	-
(Rohm et al., 2013)	Foot MI vs. Right Hand MI	Select the most reactive band power features	LDA
(Roset et al., 2014)	Hand Open MI vs. Hand Close MI	PSD from FFT with 1Hz bin	Normalized PSD z-scores & Actor-critic Reinforcement Learning Algorithm
(Vuckovic et al., 2015)	Left Hand MI vs. Right Hand MI	delta, theta, mu/alpha, beta1 (12 ~ 16), beta2 (16 ~ 24), PSD	Threshold
(Tam et al., 2011)	Left Hand MI vs. Right Hand MI	CSP	fLDA, Adaptive (Last 6 trials)
(Young et al., 2014)	Attempted Movements (Right vs. Left) vs. Rest	Determine channels with the largest r-squared values, ERD	-
(Young et al., 2015)	Left Hand MI vs. Right Hand MI vs. Rest	8 ~ 14 Hz (mu) and 18 ~ 26 Hz (beta)	-

2.3.3. Signal Processing for SMR-based BCIs

The signal processing procedure for SMR-based BCI system shown in Figure 2.11 consists of five consecutive steps such as signal acquisition, preprocessing, feature extraction & selection, classification, and application control. In this section, the state of the art in each signal processing stage was summarized from the literature review.

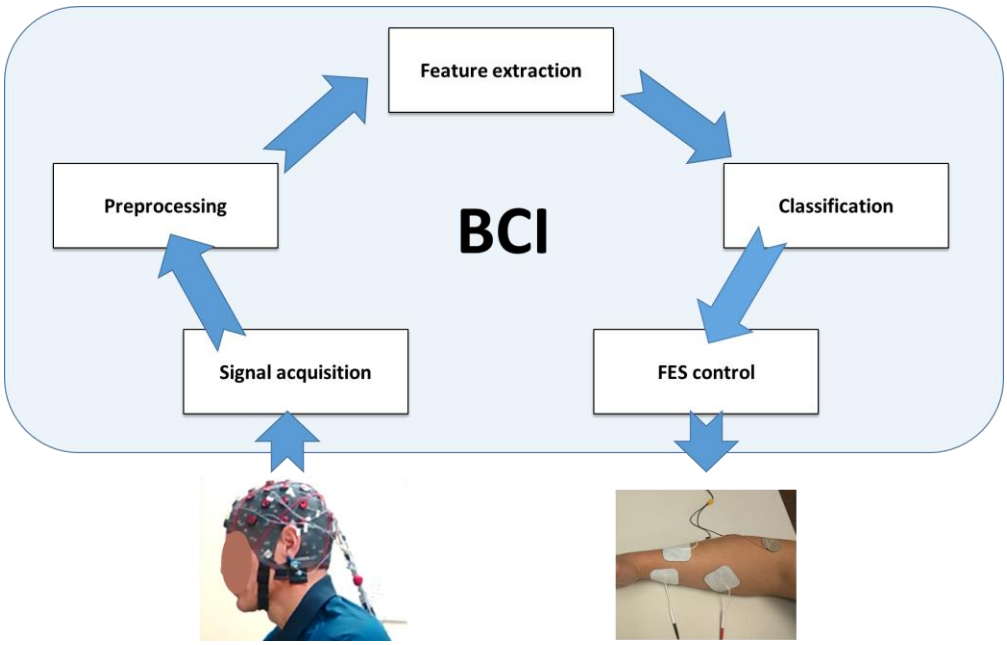
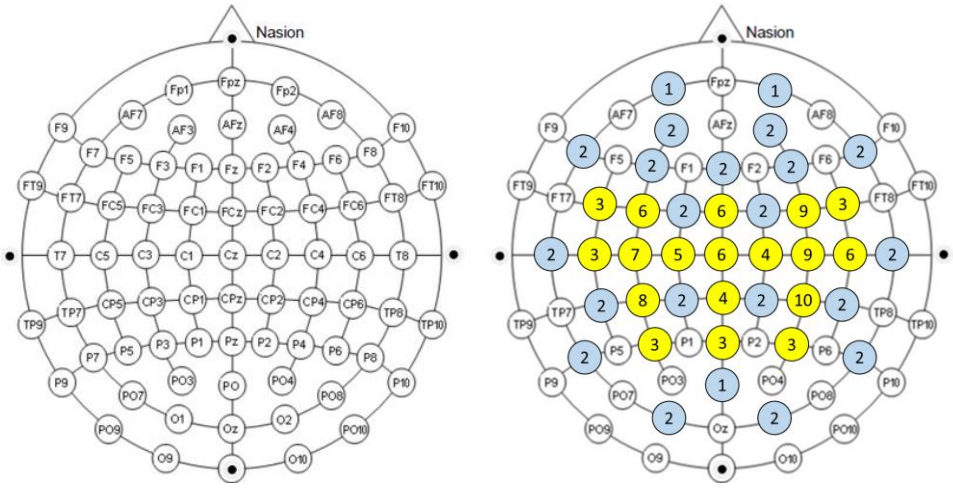


Figure 2.11. Flow diagram for signal processing

2.3.3.1. Signal Acquisition

To measure brain signals related to SMRs, proper placement of the EEG electrodes is essential. Most of the reviewed research studies measured the motor cortex area, but the specific location and number of electrodes used varied between studies. More electrodes are required for higher spatial resolution (Ferree, Clay, & Tucker, 2001), but require longer

computation time and higher complexity for signal processing (Wang, Miao, & Blohm, 2012). Furthermore, from an HF/E perspective, the use of many electrode channels could reduce user satisfaction by increasing the set-up time and the conductive gel applied to the scalp (Zickler et al., 2011). Figure 2.12 shows the layout of EEG electrodes used in 18 studies that clearly identified electrode positions in the literature review. The numbers in the circles show the number of research studies used in that location, and the yellow circles indicate the positions used in more than two studies. As can be seen in Figure 2.12 (b), most of the yellow circles are symmetrically distributed near the motor cortices, C3 and C4.



(a) **(b)**

Figure 2.12. EEG electrode montage

(a) Modified 10-10 system, (b) the counting of electrodes position: Circles colored as yellow indicate the positions were utilized in more than two research studies.

2.3.3.2. Signal Preprocessing

Once the brain signal is recorded, it is important to filter out noise, artifacts, and irrelevant brain signals to extract only SMR-related features. The EEG signal must, therefore, be inspected for unexpected contamination due to electrode drift (line noise), or motion artifacts. Thereafter, the contaminated trials should be removed through signal preprocessing procedures for further processing. One of the common techniques is to use statistical methods with rejection thresholds (Delorme, Makeig, & Sejnowski, 2001; Delorme & Makeig, 2004; Nolan, Whelan, & Reilly, 2010).

In addition, various spatial filtering methods to enhance the brain signal by increasing the signal-to-noise ratio are widely used, such as bipolar derivation, common average reference and surface Laplacian estimation techniques (Choi, Bond, Krusienski, & Nam, 2015; Hamedi, Salleh, & Noor, 2016; Pfurtscheller & Neuper, 2001). Among them, the surface Laplacian estimation has been applied to many SMR-based BCI studies that can enhance spatial EEG trace by filtering the common spatial noise among nearest-neighbor or next-nearest electrodes (Bashashati, Fatourechi, Ward, & Birch, 2007; McFarland, McCane, David, & Wolpaw, 1997; Pfurtscheller & Neuper, 1997; Wolpaw et al., 2002). The equation of surface Laplacian estimation is shown in Equation 2.1, where $V_{(i)}$ is *i*-th electrode signal and $d_{i,j}$ is the distance between electrodes *i* and *j*, S(*i*) is the set of adjacent electrode near *i*-th electrode such as anterior, posterior, left- and right-lateral, and $w_{i,j}$ is the weight parameters which is set in inverse proportion to the distance from the *i*-th electrode (McFarland et al., 2000; Schalk & Mellinger, 2010).

Equation 2.1. Surface Laplacian estimation

$$V_{Laplacian(i)} = V_{(i)} - \sum_{j \in S(i)} w_{i,j} V_{(j)} \qquad where\, w_{i,j} = \frac{\frac{1}{d_{i,j}}}{\sum_{j \in S(i)} \frac{1}{d_{i,j}}}$$

Independent Component Analysis (ICA) is also a useful technique for removing artifacts such as eye-blinking and muscle activities. The aim of ICA is to identify the best estimate of the separation matrix with the assumption the target signal and artifacts are mutually independent (Hyvärinen & Oja, 2000). ICA has the advantage of not relying on a priori knowledge or hypothesis, but it also has a disadvantage that it requires a lot of calculation time to analyze high dimensional (channel) data.

To address this issue, Principal Component Analysis (PCA) could be utilized, which is also called decomposition of the covariance matrix. PCA is a statistical procedure that transforms correlated variables into linearly uncorrelated variables and can reduce brain signal with high dimensions (channels) into lower dimensions while maintaining important features (Kayser & Tenke, 2003; Lee & Choi, 2003; Shlens, 2003). Once the dimension of the EEG data is reduced through the PCA process, the reduced dimensional signal is decomposed into maximally independent components through the ICA.

2.3.3.3. Feature Extraction and Selection

One of the major feature extraction methods for the SMR-based BCI research is to utilize Event-related Desynchronization and Synchronization (ERD/ERS), which analyzes the alpha and beta frequency bands (Pfurtscheller & Neuper, 2006; Young et al., 2015). To

compute ERD/ERS, the recorded EEG signal is divided into SMR and reference periods based on predefined timing, such as the point at which MI tasks started, then each period is transformed from time-domain data to frequency-domain data by Fast Fourier Transform (FFT) (Roset et al., 2014). Afterward, the relative band power between a reference period and an MI period of each frequency band is calculated by Equation 2.2, where M is the FFT transformed absolute power of the MI period, and R is that of the reference period.

Equation 2.2. ERD/ERS

$$ERD / ERS\ (\%) = \frac{(M - R)}{R} * 100$$

Although the range of each frequency band has a large impact on ERD/ERS features, the alpha and beta bands used in previous studies varied from study to study as shown in Table 2.9. The research studies using two bands in the literature review used a subset of 7-15 Hz for the alpha band while a subset of 13-30 Hz for the beta band. In contrast, Daly and colleagues (2009) utilized 10 bins divided by 3 Hz intervals of EEG data between 0-30 Hz rather than dividing the two bands. Reynolds et al. (2015) and Rohm et al. (2013) employed very wide frequency bands, such as 5-60 Hz and 0.5-100 Hz respectively, and then selected significant frequency bands by statistical methods. Pfurtscheller and Lopes (1999) suggested a guideline to determine the proper range of ERD/ERS bands for each subject such as ‘comparison of short-time power spectra’ and ‘determination of frequency bands dependent on the peak frequency.’ The former method should plot short-time power spectra value to find the user-specific frequency band, while the latter just calculates the ERD for each frequency sub-band to avoid inter-individual differences.

The other well-known feature extraction method used in the previous studies is Common Spatial Pattern (CSP). The CSP method transforms multichannel EEG data into a subspace using a variance matrix that can maximize discrimination between two classes (C1 and C2) (Golub, Chase, Batista, & Yu, 2016). Therefore, the use of CSP as a spatial filter can increase the subsequent classification accuracy (Nicolas-Alonso & Gomez-Gil, 2012; Pfurtscheller, Linortner, Winkler, Korisek, & Müller-Putz, 2009). The normalized covariance matrix in CSP can be calculated as shown in Equation 2.3, where trace($X_{Cx}X_{Cx}^T$) is the sum of diagonal elements of $X_{Cx}X_{Cx}^T$ (Nicolas-Alonso & Gomez-Gil, 2012).

Equation 2.3. The normalized covariance matrix in CSP

$$C_{C1} = \frac{X_{C1}X_{C1}^T}{trace(X_{C1}X_{C1}^T)}, \quad C_{C2} = \frac{X_{C2}X_{C2}^T}{trace(X_{C2}X_{C2}^T)}, \quad C_c = C_{C1} + C_{C2}$$

Afterward, the composite spatial covariance, C, and CSP projection matrix, W, can be calculated as shown in Equation 2.4, where U_c is a matrix of normalized eigenvectors, and λ is eigenvalues. The projection matrix W then transforms multi-channel EEG signals into CSP features that can help to discriminate vague spatial information evoked by MI (Elnady et al., 2015; Tam et al., 2011).

Equation 2.4. Composite spatial covariance, C, and CSP projection matrix, W.

$$C_c = C_{C1} + C_{C2} = U_c \lambda U_C^T \qquad W = U^T \sqrt{\lambda} U_C^T.$$

Although the CSP method has shown promising results to analyze SMR features, performance of CSP was greatly influenced by which frequency bands were selected similar to the ERD/ERS method (Ang, Chin, Zhang, & Guan, 2008; Novi, Guan, Dat, & Xue, 2007). One exhaustive approach is to find the optimal frequency band for each subject after examining all possible frequency bands, but this method may require a lot of time and effort to identify user-specific frequency bands. To address this issue, Novi et al. (2007) proposed Sub-band CSP (SBCSP) that first decomposes the EEG signal into multiple sub frequency bands, extracts CSP features from each sub-band, and then makes a decision based on the fused classification scores obtained using the sub-band features. The advantages of SBCSP are that it does not require exhaustive band selection procedure, as well as allows to use multiple frequency bands at the same time (Blanchard & Blankertz, 2004; Novi et al., 2007).

2.3.3.4. Classification Algorithms

One of the easiest and simplest approaches to decoding classes from extracted features is the threshold detection method (Kim et al., 2016; Pfurtscheller et al., 2005; Vuckovic et al., 2015). The threshold detection algorithm detects signals that exceed a predefined value, such as EEG potentials, FFT values, and ERD/ERS values. One of the most widely used algorithms used in MI are the Linear Discriminant Analysis (LDA) algorithms including Fisher's LDA, stepwise LDA, and shrinkage LDA (Choi, Bond, Krusienski, & Nam, 2016; Elnady et al., 2015; Looned et al., 2014; Müller et al., 2003; Tam et al., 2011). LDA sets a hyperplane that maximizes the separability between classes and minimizes the variance within classes, assuming that the training data follows multivariate normal distributions with equal covariance

matrices (Lotte et al., 2007). For example, Fisher's LDA can classify two classes with Equation 2.5, where N indicates the number of training samples, (x_i) belongs to each class (C_1 and C_2), m_1 and m_2 are class means. The slope of the hyperplane (w) is used to identify the local maxima of S, and r(w) should be maximized. Therefore, the solution is as below.

Equation 2.5. Fisher's LDA

$$m_1 = \frac{1}{N_1}\sum_{x_i \in C_1} x_i, \qquad m_2 = \frac{1}{N_2}\sum_{x_i \in C_2} x_i$$

Class means

$$\tilde{m}_1 = \frac{1}{N_1}\sum_{x_i \in C_1} w^T x_i = w^T m_1, \qquad \tilde{m}_2 = \frac{1}{N_2}\sum_{x_i \in C_2} w^T x_i = w^T m_2$$

Projected class means

$$\tilde{m}_2 - \tilde{m}_1 = w^T (m_2 - m_1)$$

Difference between projected class means

$$J(w) = \frac{(\tilde{m}_2 - \tilde{m}_1)^2}{\tilde{s}_1^2 + \tilde{s}_2^2} = \frac{w^T S_B w}{w^T S_w w} \text{, where } \begin{array}{l} S_w = S_1 + S_2 \\ S_B = (m_2 - m_1)(m_2 - m_1)^T \end{array}$$

Ratio of difference of projected means over total scatter

$$w^* = S_w^{-1}(m_2 - m_1)$$

The optimal projection matrix

Support Vector Machine (SVM) is one of the most popular classifiers used in MI. SVM utilizes the maximum margin linear classifier, which is the width of the boundary strip between classes, to minimize the error rate. Therefore, SVM is robust to over-filtering and less sensitive to high dimensionality compared to LDA. If a training dataset with two classes is defined as in

Equation 2.6 (1), then the data points on each marginal boundary X^+ and X^- satisfy Equation 2.6 (2). The margin width, M, can be calculated with Equation 2.6 (3). Equation 2.6 (4) can maximize M.

Equation 2.6. SVM

(1)
$$\text{For } y_i = +1, \quad \mathbf{w}^T\mathbf{x}_i + b \geq 1$$
$$\text{For } y_i = -1, \quad \mathbf{w}^T\mathbf{x}_i + b \leq -1$$

(2)
$$\mathbf{w}^T\mathbf{x}^+ + b = 1$$
$$\mathbf{w}^T\mathbf{x}^- + b = -1$$

(3)
$$M = (\mathbf{x}^+ - \mathbf{x}^-)\cdot\mathbf{n}$$
$$= (\mathbf{x}^+ - \mathbf{x}^-)\cdot\frac{\mathbf{w}}{\|\mathbf{w}\|} = \frac{2}{\|\mathbf{w}\|}$$

(4)
$$\text{maximize } \frac{2}{\|\mathbf{w}\|} \equiv \text{minimize } \frac{1}{2}\|\mathbf{w}\|^2$$

The quadratic programming with linear constraints as shown in Equation 2.6 (5) can be solved as Equation 2.6 (6) by the Lagrangian dual problem.

(5) $$\text{minimize } L_p(\mathbf{w}, b, \alpha_i) = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{i=1}^{n}\alpha_i\left(y_i(\mathbf{w}^T\mathbf{x}_i + b) - 1\right) \quad \textbf{s.t. } \alpha_i \geq 0$$

(6) $$g(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b = \sum_{i\in \mathrm{SV}}\alpha_i\mathbf{x}_i^T\mathbf{x} + b$$

However, due to the nature of EEG signals, there are some critical issues such as ‘noisy signal and outliers,’ ‘high dimensionality,’ ‘non-stationarity,’ and ‘small training sets’ (Lotte et al., 2007). Due to these issues, we cannot guarantee that the classifier will elicit good results

most of the time (Polikar, 2006; Sun, Zhang, & Zhang, 2007). One approach to address this issue is ensemble methods in which the outputs of the multiple classifiers are combined to make a single decision that could improve performance of each classifier (Polikar, 2006). Polikar defined two key components of an ensemble system as "*First, a strategy is needed to build an ensemble that is as diverse as possible. Some of the more popular ones, such as bagging, boosting, AdaBoost, ... A second strategy is needed to combine the outputs of individual classifiers that make up the ensemble in such a way that the correct decisions are amplified, and incorrect ones are cancelled out"* (Polikar, 2006, *p.27*). In this study, the second strategy is adopted by combining the class outputs of both LDA and SVM classifiers to improve classification accuracy and robustness. The author listed three combining methods which could be applied to this study including (1) majority voting, (2) weighted majority voting, and (3) behavior knowledge space. Among them, the weighted majority voting method was selected, because performance and robustness of each feature within the same classifier, as well as that of each classifier, could be varied from subject to subject. The final decision of the ensemble method with the weighted majority voting by combining the features of LDA and SVM can be calculated by Equation 2.7.

Equation 2.7. Ensemble decision with weighted majority voting

$$\sum_{t=1}^{T} w_t d_{t,J} = \max_{j=1}^{C} \sum_{t=1}^{T} w_t d_{t,j}$$

Where,

t = the type of classifiers (1 = LDA, 2 = SVM)

T = the number of classifiers (T = 2)

j = the type of classes (j = 1 to 2)

C = the number of classes (C = 2)

w_t = the predefined weight of classifier t

$d_{t,J}$ = If t^{th} classifier chooses class j, then $d_{t,j}$ = 1, and = 0, otherwise

The accuracy (p) of each classification method including LDA, SVM, and ensemble methods can be assessed by the significance of the accuracy (Noirhomme et al., 2014). The normal distribution can be used to approximate the binomial distribution, but this approximation can be valid only if the number of trial (N) is large enough such as $N \geq 5 / p / (1 - p)$ (Berrar, Bradbury, & Dubitzky, 2006; Brownlee & Brownlee, 1965; Rosner, 2015). To estimate the binomial lower bound of the accuracy, Jeffreys' Beta distribution is usually utilized (Berrar et al., 2006), and can be calculated by Equation 2.8.

Equation 2.8. True error rate of binomial classification

$$\lambda \approx \left\{ a + \frac{2(N-2m)z\sqrt{0.5}}{2N(N+3)} \right\} - z\sqrt{\frac{a(1-a)}{N+2.5}}$$

Where,

λ = the true error rate of binomial classification

α = the expected accuracy (0.5)

N = the number of trials

m = the expected number of correct trials (N/2 with α = 0.5)

z = z-score based on the standard normal distribution (1.65; p = 0.05; one-sided)

For example, the true chance level, the binomial lower bound, can be estimated as 62.7% with 40 trails, and this lower bound is much higher than the conventional chance level 50%. Table 2.10 shows the true error rate of binomial classification for different numbers of trials, and these rates were utilized as lower bounds to set the true chance level for hypotheses in Section 2.4.

Table 2.10. True chance level for different numbers of trials

# of trials	True chance level (%)
30	64.43
60	60.40
120	57.43
240	55.28

2.3.4. Limitations of Current Research

From the systematic literature review, five main limitations of current SMR-based BCI studies have been identified as follows: (1) the ambiguous MI instruction given during training which not only increases the subjective mental workload but also negatively affects SMR performance due to incorrect or inconsistent MI tasks; (2) the lack of research that investigated different MI tasks in the same limb, such as imagining opening and closing in a single hand; (3) the lack of studies utilizing SMR features as a criterion to either stop or keep FES by voluntary MI-evoked SMRs, and (4) the unclear frequency band selection procedure for extracting SMR features that varied from study to study.

These limitations might impede a wide application of SMR-based BCI-controlled FES systems due to (1) long training periods due to ambiguous instruction for MI tasks; (2) low classification accuracy of a 2-class MI task in a single hand, and (3) difficulties in applying SMR features to either stop or keep FES.

2.4. Research Questions and Hypotheses

2.4.1. Hypothesis in Study 1

The main objectives of Study 1 were to identify appropriate FES electrode placement that can generate natural hand and wrist movements, and user-specific FES parameters which could minimize perceived muscle pain and discomfort by developing a FES platform. Once proper FES electrode placement was determined, a systematic FES parameter setting procedure was applied to identify user-specific FES parameters including pulse width, pulse rate, and current amplitude. Afterward, participants were asked to answer the degree of perceived muscle pain and discomfort corresponding to electrical stimulation using various combinations of parameters, and the effects of each combination of FES parameters on perceived muscle pain and discomfort were evaluated.

The results of Study 1 addressed the following question.

- Does the application of user-specific FES parameters reduce perceived muscle pain and discomfort rather than that of arbitrarily chosen FES parameters?

Therefore, the following hypothesis was made.

- **H1** The application of the user-specific FES parameters will significantly decrease perceived muscle pain and discomfort than that of the fixed FES parameters.

2.4.2. Hypotheses in Study 2

Study 2 addressed four main limitations of current research studies, as identified in the literature review: (1) unstructured SMR training guidelines; (2) the lack of studies that classify a 2-class MI task in a single hand; (3) the lack of studies utilizing voluntary motor intentions to stop FES, and (4) unclear frequency band selection for SMR.

In Study 2, a synchronous, cue-based BCI experiment was conducted with stroke and TBI patients training with different MI tasks (slow one-time grasp and fast cyclic opening). After the experiment, the brain signals were analyzed to evaluate the feasibilities of decoding a 2-class MI task in a single hand, and utilizing SMR features to stop or keep FES by voluntary intentions. Moreover, three classification methods including LDA, SVM, and ensemble methods were evaluated to identify that the ensemble method can improve the classification accuracy by combining two algorithms.

The results of Study 2 addressed the following questions:

- Is it feasible to classify a 2-class MI task such as grasping or opening in a single hand?
- Is it feasible to use SMR features evoked by voluntary MI to stop or keep FES?
- What effect does the existence of electrical stimulation have on task performance?
- Will the ensemble algorithms increase the classification accuracy when compared to each separate classification algorithm?

Therefore, the following hypotheses were made:

- **H2.1** The classification accuracy to classify a 2-class MI task in a single hand will be significantly higher than the true chance level.
- **H2.2** The classification accuracy to decoding voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs will be significantly higher than the true chance level.
- **H2.3** The classification accuracy of the ensemble method will be significantly higher than that of the LDA and SVM algorithms.

2.4.3. Hypotheses in Study 3

The objective of Study 3 was to evaluate the feasibility of the proposed BCI-controlled FES system in online experiments. In this experiment, participants conducted sequential tasks with fixed order such as opening a hand, grasping, holding, and dropping a ball.

In this experiment, the effects of the existence of electrical stimulation during MI tasks (No-FES vs. Yes-FES) and the application of the adaptive learning method (before-learning vs. after-learning) on task performance were evaluated.

The results of Study 3 addressed the following questions.

- Is it feasible to use the proposed SMR-based BCI-controlled FES system in an online experiment?
- Does the existence of electrical stimulation affect task performance?
- Does the application of adaptive learning affect task performance?

Accordingly, the following hypotheses were made:

- **H3.1** The classification accuracy will be significantly higher than the true chance level.
- **H3.2** Task performance between two periods, No-FES and Yes-FES period, will be significantly different.
- **H3.3** Task performance after applying adaptive learning will be significantly greater than before.

3. STUDY 1: DEVELOPMENT OF AN FES PLATFORM

From the systematic literature review of the FES systems used in current research studies in Section 2.2.4, three important issues were identified as follows: (1) FES units used in previous studies did not support real-time computer control or were not readily available in the United States; (2) FES electrode positions were not clearly defined and were not considered anthropometric data, such as forearm length and mass, and 3) FES parameters, which are important to realize the natural movement of hand and wrist while minimizing perceived muscle pain and discomfort, were usually set arbitrarily with fixed parameters.

These limitations make it difficult for many researchers to apply FES systems to SMR-based BCIs. This is because (1) it is not easy to find or build an FES platform with essential functions, and (2) it requires much effort and experience in finding appropriate FES electrode placement and parameters. Furthermore, there is a lack of research that takes into account the HF/E perspectives, such as user satisfaction in applying FES systems.

Study 1 consists of two phases to address above issues by: (1) developing a customized FES platform using inexpensive off-the-shelf Transcutaneous Electrical Nerve Stimulation (TENS) units; (2) considering anthropometric data to provide adequate initial FES electrode coordinates, and (3) proposing a systematic parameter determination procedure to enhance user satisfaction. Figure 3.1 illustrates the framework of Study 1 with two phases. The results of Study 1 are used in the following Studies 2 and 3.

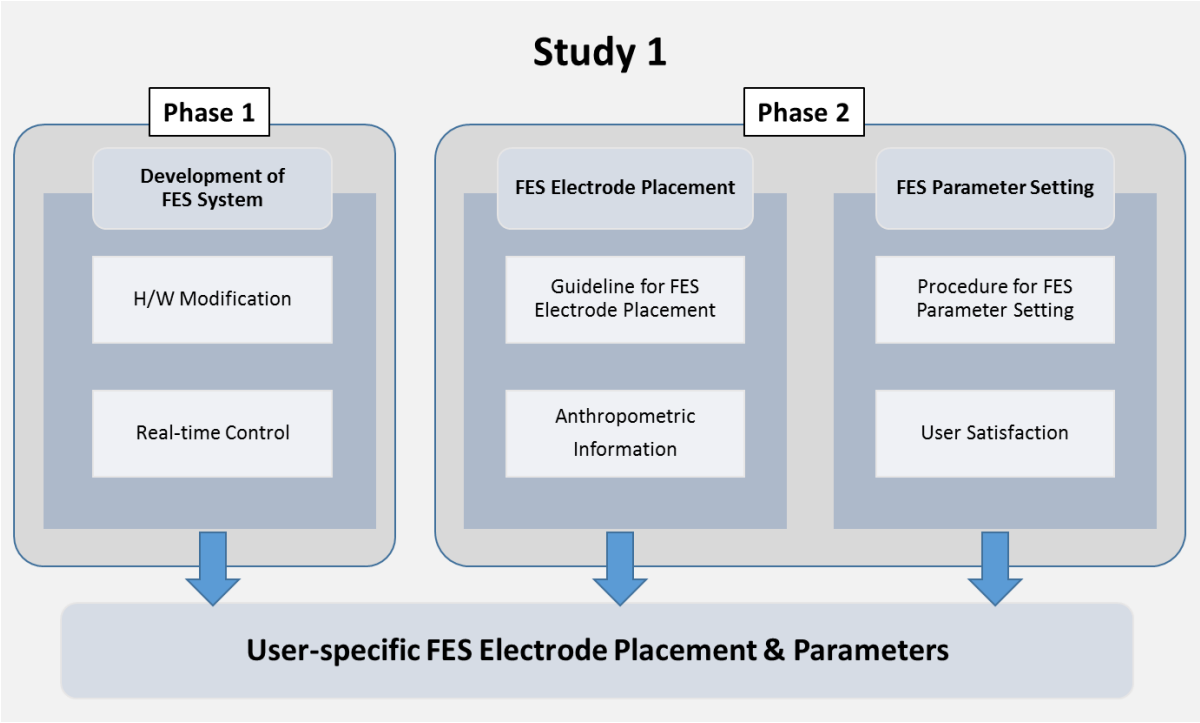


Figure 3.1. Framework of Study 1 with two phases

3.1. Phase 1: Development of an FES System

3.1.1. Objectives

Phase 1 aims to meet the requirement of the FES units for SMR-based BCI research identified in Section 2.2 by building a customized FES system with commercially available TENS units. The proposed FES system has the seven essential features including (1) the number of electrodes, (2) pulse rate, (3) pulse width, (4) current amplitude, (5) stimulation waveform, (6) ramp time, and (7) electrode pad size and shape. Furthermore, the FES system in this study can support real-time computer control to implement physiological feedback according to the motor intention from the brain signal.

3.1.2. Characteristics of TENS 3000

TENS was originally designed to relieve pain by masking the electrical activity of the nerves (Doucet et al., 2012; Levin & Hui-Chan, 1992). Most TENS units are able to control three parameters of electrical stimulation such as pulse rate, pulse width, and current amplitude through surface electrodes. The TENS unit supports a different number of FES electrodes depending on the product, and it can adjust various parameter range with analog or digital control system as shown in Table 3.1.

Table 3.1. Functionalities of selected TENS units
(Retrieved from http://www.tensunits.com/; last accessed 7/3/2016)

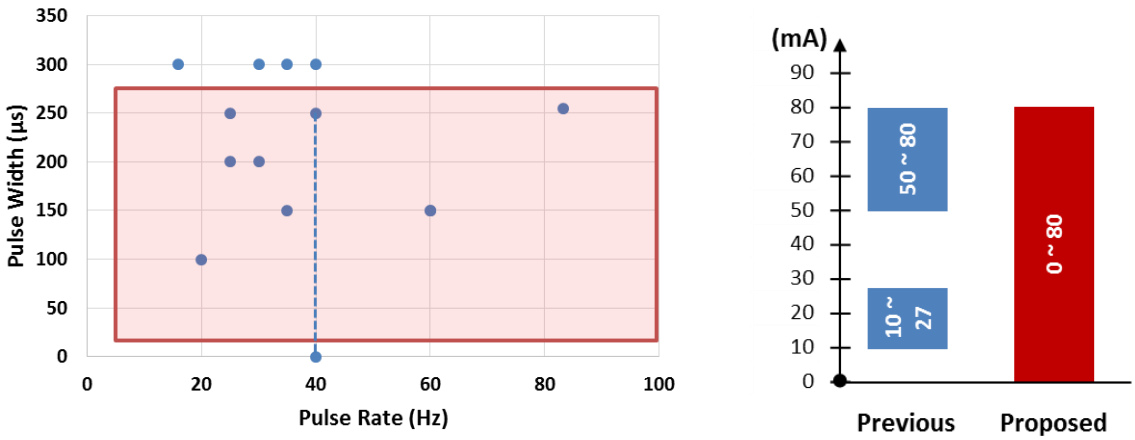
Name	Channel	Pulse Rate (Hz)	Pulse Width (μs)	Current Amplitude (mA)	Digital or Analog
The Omega Tens	2	1 ~ 150	50 ~ 400	0 ~ 100	Digital
TU-7000	2	2 ~ 150	30 ~ 260	0 ~ 100	Digital
PMT-Uneo	2	1 ~ 150	50 ~ 300	0 ~ 100	Digital
InTENSity	2	1 ~ 150	50 ~ 300	0 ~ 105	Digital
Twin Stim Plus	4	2 ~ 150	50 ~ 300	0-80	Digital
ProM-355	2	20 ~ 160	50 ~ 260	0 ~ 80	Digital
TENS-3000	2	2 ~ 150	30 ~ 260	0 ~ 80	Analog

In this study, four TENS 3000 units (Current Solutions, LLC, Austin, TX) were selected to build the FES system, as this model was commercially available at Amazon.com (Amazon.com, Inc., Seattle, WA) at an inexpensive price (less than $30 per unit) at the time of this study (2016). As shown in Figure 3.2, the TENS 3000 has four analog knobs, each of which has the following functions: Two knobs labeled “1” and “2” are for current amplitude control of two electrical stimulation channels, “3” and “4” are for pulse width and pulse control, respectively. The TENS 3000 controls the stimulation parameters by turning these knobs to adjust analog potentiometers, which can be easily replaced with a digital potentiometer and an external control board for real-time control.

Figure 3.2. TENS 3000

Knobs labeled "1" and "2" are for current amplitude control of channel 1 and 2, respectively, while "3" and "4" are for pulse width and pulse rate, respectively.

Each TENS 3000 unit can support two electrical stimulation channels with independent current amplitude control, and the proposed FES system can easily increase the number of electrical stimulation channels by synchronizing multiple in tandem. In addition, a TENS 3000 unit can generate electrical stimulation with a pulse rate of 2-150 Hz, current amplitude of 0-80 mA, and pulse width of 30-260 μs as shown in Figure 3.3.



(a) **(b)**

Figure 3.3. Parameter ranges supported by the proposed FES system

(a) Blue dots and line indicate pulse rate and width used in the previous research, and a red box shows the range of parameters supported by the proposed FES system. (b) Blue boxes represent the range of current amplitude used in the previous research, and a red box indicates that of current amplitude supported by the proposed FES system.

The red box in Figure 3.3 (a) represents the ranges of pulse rate and pulse width supported by the proposed FES system, and the blue dots indicate the parameters used in the previous studies. The proposed system can support most of the parameters previously used except for pulse widths of more than 260 µs as shown. Since muscle contraction is achieved by modulating the current amplitude and/or pulse width (Crago et al., 1980; Quandt & Hummel, 2014), this limited pulse width range can be overcome by increasing the current amplitude.

The TENS 3000 unit is capable of generating asymmetric biphasic stimulation waveform. As mentioned in Section 2.1.4, many research studies have identified the advantages of asymmetric biphasic pulses in comparison to symmetrical stimulation, which not only allows more effective muscle control but also leads to less muscle fatigue (Keller et

al., 2005; Lawrence, 2009; Ragnarsson, 2008). The Asymmetric biphasic stimulation waveform generated by TENS 3000 is shown in Figure 3.4.

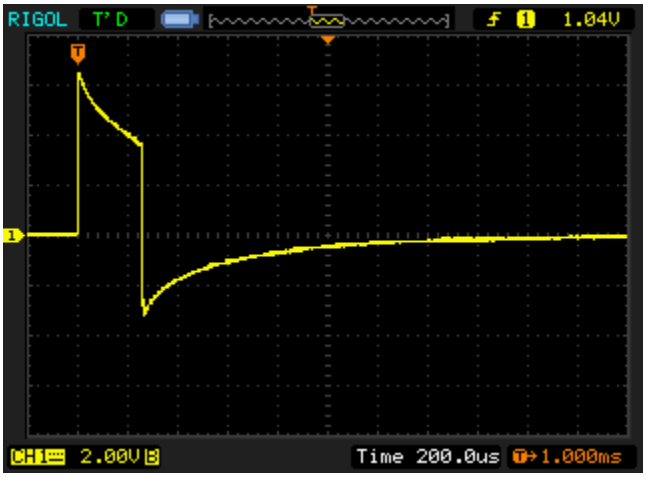


Figure 3.4. Asymmetric biphasic stimulation waveform generated by TENS 3000

Since TENS 3000 employs a standard 2 mm diameter lead wire with a pin connector, the proposed FES system is able to utilize various sizes and shapes of electrode pads identified in Section 2.1.4. Finally, although the TENS 3000 itself does not support the ramp time function of the electrical stimulus, this feature was implemented with a gradual increase in pulse rate or current amplitude via real-time computer control.

3.1.3. Modification of TENS 3000

For real-time computer-controlled functionality, the analog potentiometers of the TENS 3000 units have been replaced by digital potentiometers, and these digital potentiometers are controlled via an external control board. For current amplitude control, the

existing analog potentiometers were replaced with two AD5160 I2C digital potentiometers (Analog Devices, Inc., Norwood, MA), which allows the current amplitude of each electrical stimulation channel to be adjusted between 0-80 mA with a resolution of 312.5 μA. Similarly, a digital potentiometer AD5262 (Analog Devices, Inc., Norwood, MA) was used for both pulse rate and pulse width control, allowing to adjust pulse rate between 0-150 Hz in 1 Hz steps and pulse width between 30-260 μs with 1 μs increments.

These digital potentiometers were then controlled in real-time via Arduino Uno, which was connected to a personal computer (PC) to set TENS parameters for FES, such as pulse rate, pulse width, and current amplitude, without manual intervention. Arduino is *"a family of microcontrollers (tiny computers) and a software creation environment that makes it easy for you to create programs (called sketches) that can interact with the physical world."* (Margolis 2011, p. xiii).

Figure 3.5 shows the development process for modifying the TENS unit for the FES system. Figure 3.5 (a) presents TENS 3000 with four analog knobs for each parameter control, and Figure 3.5 (b) shows digital potentiometers replacing the analog potentiometers and Arduino Uno enabling real-time computer control of the digital potentiometers. Figure 3.5 (c) displays a prototype of the modified TENS unit with Arduino Uno and digital potentiometers on a solderless breadboard. Figure 3.5 (d) shows the parts on the breadboard were assembled on a custom printed circuit board to simplify wiring and increase the robustness of the system.

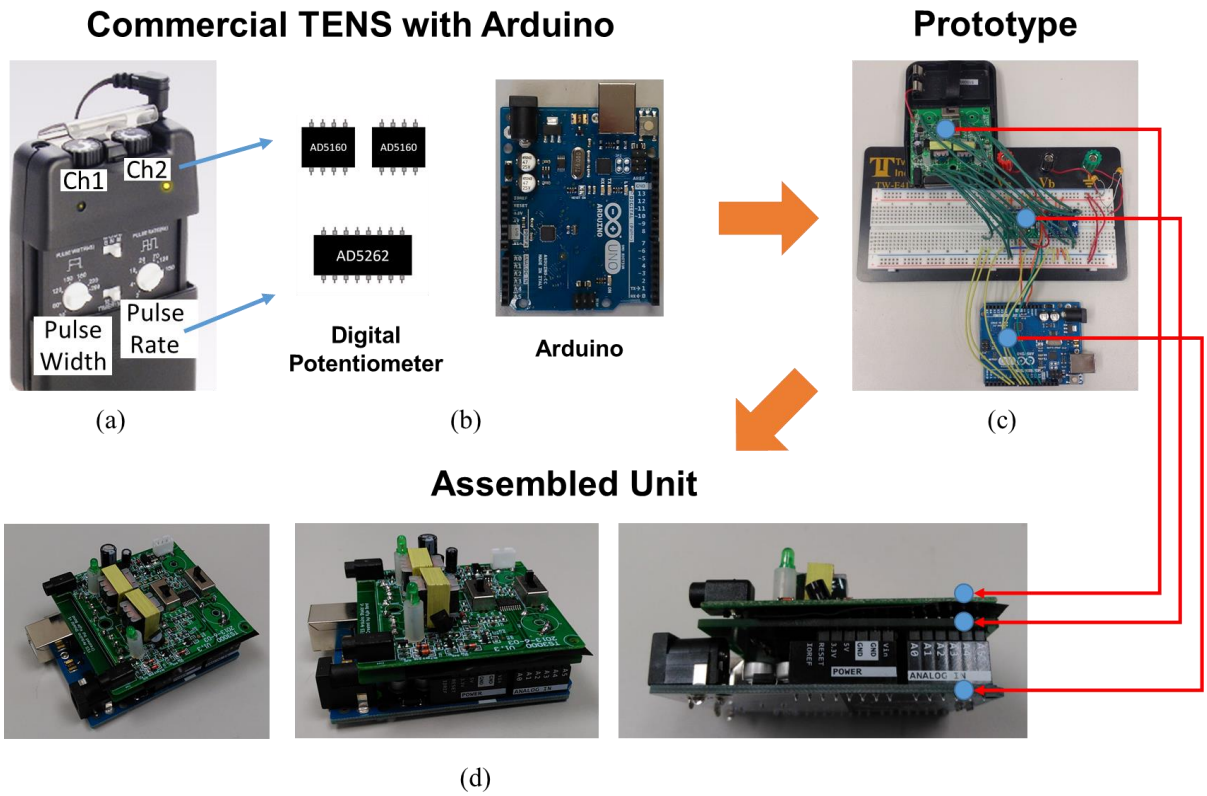


Figure 3.5. Development process of the proposed FES units

(a) TENS 3000 with four analog knobs. (b) Three digital potentiometers and Arduino Uno. Two AD5160 parts are for current amplitude control and the AD5262 for both pulse width and rate control. (c) The prototype of the modified TENS unit with Arduino Uno and digital potentiometers on a solderless breadboard. (d) The assembled unit onto a custom printed circuit board.

3.1.4. Results

In Phase 1, four inexpensive and off-the-shelf TENS devices have been modified to enable real-time computer control as well as to support these essential features by replacing analog potentiometers with digital potentiometers. Through these modifications, the proposed FES system can support seven important features in FES operation identified in Section 2.1.4 and is also capable of controlling multiple FES electrodes to derive natural hand and wrist movements by synchronizing four TENS units in tandem. Through these functions, the

proposed FES system meets the essential requirements of SMR-based BCI research. Table 3.2 summarizes the functionalities of the proposed FES system, and it also demonstrates the role of each function.

Table 3.2. Functionalities of the proposed FES system

Feature	Capability	Role
Electrodes	Up to 8 channels	To stimulate multiple muscles for natural hand and wrist movements
Pulse Rate	2 ~ 150 Hz	To apply user-specific parameters
Pulse Width	30 ~ 260 μs	To apply user-specific parameters
Current Amplitude	0 ~ 80 mA	To apply user-specific parameters
Stimulation Waveform	Asymmetric biphasic	To minimize potential risks such as muscle fatigue and muscle damage
Ramp Time	Supported via real-time computer control	To enhance user's comfort
Electrode Pad Type	Any pads with a standard 2.0mm connection	To effectively deliver electrical stimulation to muscles of various sizes
Real-time computer control	Supported	For control over SMR-based BCIs

The proposed FES system is controlled by a PC, and the control mechanism is as follows. First, an Arduino Uno, which allows real-time computer control of the replaced digital potentiometers, is connected to a PC via a USB port. Afterward, MATLAB (MathWorks, Natick, MA) initiates a serial connection between the PC and Arduino Uno, and the Arduino Uno waits for incoming commands from the serial port. When the Arduino Uno receives a control command generated by MATLAB to change the stimulation parameters, the Arduino Uno applies parameters of TENS units according to the incoming commands by adjusting the

impedance of the digital potentiometers. The TENS unit then generates electrical stimuli according to the set impedance of the digital potentiometer and transmits them through the FES electrodes to induce muscle contraction. Figure 3.6 shows the control mechanism flow diagram of the proposed FES system.

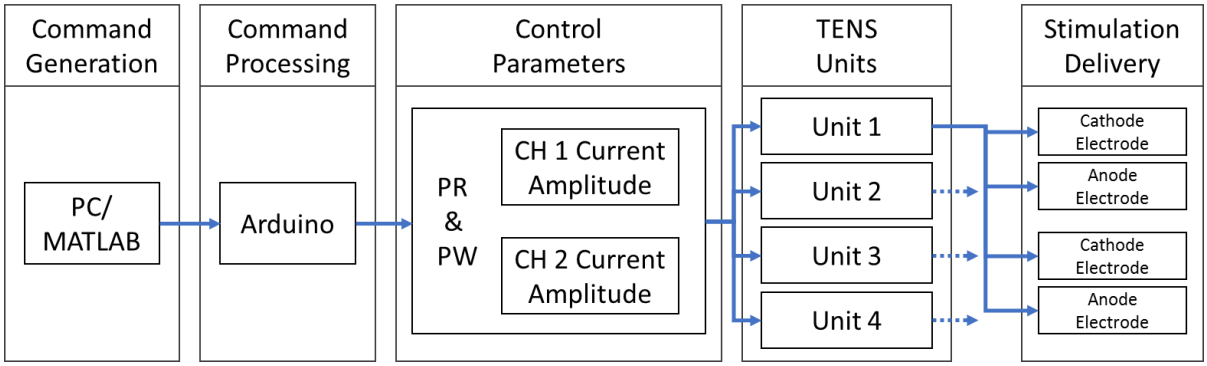


Figure 3.6. Control mechanism flow diagram of the proposed FES system

3.2. Phase 2: Determination of FES Electrode Placement and Parameters

3.2.1. Objectives

The objectives of Phase 2 are to address the issues identified in 2.2.4 including (1) lack of guidelines to help identify proper electrode placement, and (2) lack of research using user-specific pulse rate and pulse width to improve user satisfaction by minimizing perceived muscle pain and discomfort.

To find appropriate FES electrode placement, most studies relied on manual palpation without considering the length and mass of the forearm. It may be inaccurate and time-consuming for researchers or practitioners who are not an expert in muscle anatomy to find an adequate position. To address this issue, the feasibility of using anthropometric data was investigated to determine proper initial FES electrode placement without detailed knowledge of muscle anatomy.

In addition, most of the current research studies used fixed FES parameters for all participants, although the user-specific FES parameters are important in order to minimize discomfort and to maximize user satisfaction (Doucet et al., 2012). To address this issue, a systematic FES parameter setting procedure was proposed to identify user-specific FES parameters including pulse rate, pulse width, and current amplitude. Afterward, subjective assessments were analyzed to evaluate whether the application of user-specific FES parameters could reduce perceived muscle pain and discomfort compared to using fixed parameters. The results of Phase 2 were then utilized for the following SMR-based BCI studies.

3.2.2. Participants

A total of 8 stroke patients (5 males and 3 females, average age 46.0 ± 13.5 years) were recruited from local rehabilitation centers and clinics. All studies were reviewed and approved by the Institutional Review Board of North Carolina State University. The participants received monetary compensation ($15/hour) for participation, and any participants who were displeased during the studies could cease at any time, but no one had chosen to withdraw the study until the studies were complete.

The number of the participants in this study was similar to or higher than that in the 15 reviewed studies except for two studies in which patients were recruited for the experiments as shown in Table 3.3.

Table 3.3. The numbers of patients recruited from the previous studies

Studies	The number of patients
(Daly et al., 2009)	1
(Elnady et al., 2015)	9
(Tan et al., 2011)	9
(Kim et al., 2016)	15
(Liu et al., 2014)	3
(Mukaino et al., 2014)	1
(Pfurtscheller et al., 2003)	1
(Pfurtscheller et al., 2005)	1
(Rohm et al., 2010)	1
(Rohm et al., 2013)	1
(Roset et al., 2014)	2
(Vuckovic et al., 2015)	2
(Tam et al., 2011)	5
(Young et al., 2014)	1
(Young et al., 2015)	16

Although TENS units used in the proposed FES system were approved by the Food and Drug Administration as a commercial medical device, precautions for the use of electrical stimulation should still be considered. For example, electrical pulses from the TENS units may cause problems with a cardiac pacemaker or implanted drug pump. To avoid any potential risks, participants were asked to fill out the FES Safety Screening Questionnaire (See Appendix A) at the time of initial contact, and participants with symptoms listed on the questionnaire were excluded prior to the experiment. In addition, patients who suffered from significant cognitive, perceptual, and communication difficulties were excluded, because participants should be able to understand instructions, follow the guidelines, and provide feedback during the experiments.

The inclusion criteria in this study were: (1) suffering from upper limb hemiparesis, weakness on one side of the body, the most common impairment after stroke or TBI; (2) in the chronic state of stroke, the condition of a stroke patients persisted without recurrent strokes for more than three months, to prevent the potential risk of recurrent stroke (only for stroke patients), and (3) having normal sensitivity to feel pain and discomfort on the impaired forearm. Table 3.4 summarizes demographic and clinical information of participants.

Table 3.4 Demographic and clinical information of participants

ID	Age	Gender	Affected side	Symptom	Occurrence (YYYY/MM)
S01	64	Female	Left	Stroke	2016/08
S02	20	Male	Right	TBI	2012/09
S03	52	Female	Right	Stroke	2014/02
S04	55	Male	Left	Stroke	2014/04
S05	56	Male	Left	Stroke	2013/05
S06	50	Male	Right	Stroke	2013/01
S07	33	Male	Right	TBI	2011/04
S08	38	Female	Right	TBI	2013/12

3.2.3. Preparations

When participants arrived at the site, they were provided a detailed overview of the experiment. When participants agreed to participate in the study, they were asked to sign an informed consent form and to complete a demographic questionnaire, and their length of elbow-wrist and circumference of the impaired forearm were measured. For the consistent measurement of the anthropometric data, standard measurement description suggested by Gordon et al. (1989) followed (See Appendix B and C).

FES delivers electrical stimulation onto the skin, which does not cause much damage to the muscles under the skin because it has a very high electrical resistance. However, if the conductivity of the electrode is not constant, then electrical stimulation would be concentrated at a certain location that could cause muscle pain and discomfort. Therefore, appropriate skin preparation is essential to maintain good conductivity between the skin and each electrode, and

the skin preparation process has been performed according to Axelgaard's guidelines (Axelgaard Manufacturing Co., Fallbrook, CA) before the experiment (see Appendix D). The total preparation time including the questionnaire took about 30 minutes.

3.2.4. Apparatus

A tape measure was used to measure the elbow-wrist length and the forearm circumference. For consistent measurement among participants, the standard measurement guideline of anthropometric data suggested by Gordon et al. (1989) was followed. A 1 cm grid-printed transparent film was also used to record the coordinates of the electrodes placed on the forearm. To determine an appropriate FES amplitude to induce sufficient grasping force, participants were asked to hold a small ball, which would be used in the following study under the SMR-based BCI system.

3.2.5. Procedures

The experimental procedure in Phase 2 consists of two steps: finding appropriate FES electrode placement and identifying user-specific FES parameters. To find the proper FES pad position, an initial electrode position was determined by manual palpation, and then a set of surface, self-adhesive FES electrode pads were attached to the selected location. The electrical stimulation using the predefined FES parameters was then delivered to the impaired forearm by the FES system and evaluated the movement of the hand and wrist generated by the stimulus. The predefined parameters were the pulse rate of 35 Hz and the pulse width of 220

μs, which is the average value from the literature review, and current amplitude increased gradually until either sufficient muscle contraction was achieved, or the stimulation was no longer comfortable. If the selected FES electrode location was not adequate, then the electrode was moved around the initial location and re-evaluated. In this study, adequate electrode placement was defined by the coordinates at which FES could perform the following actions: (1) opening wide enough to be ready to hold a small ball, at least 4 inches between thumb-tip and nearest fingertip, and (2) grasping with enough strength to lift the ball properly.

Once adequate electrode placement was determined, the location of the center of the FES electrodes was marked on the transparent film with a printed 1-cm grid. The Ulnar Styloid Process (USP) and Radial Styloid Process (RSP) were set as reference positions for projecting the FES electrodes attached to the forearm into 2-dimensional space, similar to Lawrence (2009). The line between USP and RSP was defined as the X-axis, and the middle (and thickest part) of the forearm was set as the Y-axis. A 2-dimensional space constituted by the X and Y axes on the transparent film printed 1-cm grid is shown in Figure 3.7.

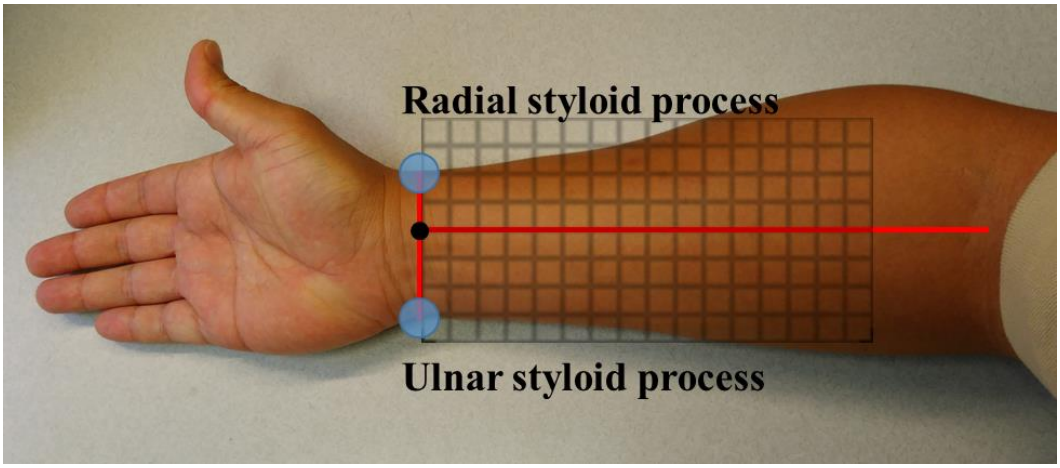


Figure 3.7. 2-dimensional space to record adequate electrode position

A total of four pairs of X and Y coordinates were measured and recorded, with two sets for grasping and the other two sets for opening. Once the adequate FES electrode coordinates were defined, then the coordinates were normalized with respect to anthropometric data. The normalized electrode coordinates were used to verify the feasibility of using anthropometric data to determine proper FES electrode placement. The experiment for determining adequate FES electrode placement lasted about 30 minutes for four different muscle groups, such as Finger Extension (FE), Finger Flexion (FF), Wrist Extension (WE), and Wrist Flexion (WF).

The second step of Phase 2 was to identify user-specific FES parameters through a systematic FES parameter setting procedure. This step examined nine combinations of two parameters, pulse rate and pulse width, which are shown in Table 3.5. The combinations were replicated, and all 18 trials were randomized to avoid potential order effects. Current amplitude of all combinations were gradually increased until either maximum muscle contraction was achieved, or the stimulation was no longer comfortable. In the table, 35 Hz for pulse rate and 220 μs for pulse width were set as references which are the average values from the literature review.

Table 3.5. Combinations of FES parameters

Pulse Rate	Pulse Width
	180
30	220
	260
	180
35	220
	260
	180
40	220
	260

After applying each combination, participants were asked to assess perceived muscle pain and discomfort with a modified 100-point Visual Analogue Scale (VAS) (Forrester & Petrofsky, 2004; Miller et al., 2010). To measure the subjective assessment properly, a computerized VAS software was built. In the VAS software, participants were asked to select the perceived scale between "No Pain and Discomfort" to "Very Severe Pain and Discomfort," then the marked values were recorded. The interface of VAS software is shown in Figure 3.8.

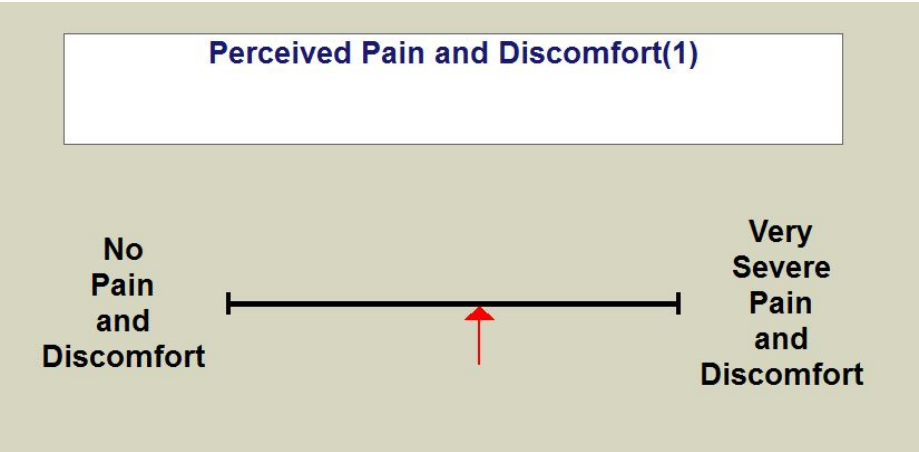


Figure 3.8. Computerized VAS assessment interface

After the systematic FES parameter setting procedure, the five parameter combinations with the five lowest VAS scores were selected as candidates. Then, FES was applied again using these parameters to determine the user-specific FES parameters which could minimize perceived muscle pain and discomfort, as well as could open wide enough to be ready to hold a small ball and be strong enough strength to lift the ball properly. Once the user-specific parameters were identified, the proposed procedure was validated by analyzing the VAS scores between the user-specific and predefined parameters.

The experiment to determine user-specific FES parameters took about 20 minutes, including a total of 36 trials (18 trials for each motion, such as grasping and opening) with the subjective assessment after each trial. During these trials, participants had the opportunity to ask questions and address any concerns they might have under the FES system.

After Study 1, participants were asked to complete a post-experiment questionnaire (See Appendix E). The completion time of Study 1 was one and half hours, including time for prior surveys, preparations, the experiment in Phase 2, and the post questionnaire.

3.2.6. Independent and Dependent Variables

Two independent variables (IVs), such as pulse rate and pulse width, were manipulated in the experiments for each motion including grasping and opening. All IVs had three levels as shown in Table 3.5. The raw scores obtained on VAS were standardized for each participant by z-transformation to control the variation between participants due to the differences in subjective assessment (Fischer & Milfont, 2010; Kane, Bershadsky, Rockwood, Saleh, &

Islam, 2005). The standardized VAS score were calculated by Equation 3.1 and used as a dependent variable (DV).

Equation 3.1. Standardized VAS score

$$Standardized\ VAS\ Score = \frac{VAS - VAS\_mean_{participant}}{VAS\_standard\ deviation_{participant}}$$

3.2.7. Experiment Design and Statistical Analysis

Since the experiment was a balanced 3 x 3 within-subject design with one DV for each motion (grasping and opening) with participant as a blocking variable, a univariate Analysis of Variance (ANOVA) model was set as Equation 3.2 to evaluate the main effect of pulse rate and pulse width, and the interaction effect between two IVs. Table 3.6 shows degree-of-freedom (DF) for each source in the model.

Equation 3.2. Experimental model for Study 1

$$y_{ijkl} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + B_k + \varepsilon_{ijkl}$$

where

i (= 1 to 3) indexes pulse rate levels

j (= 1 to 3) indexes pulse width levels

k (= 1 to 8) indexes the subjects

l (= 1 to 2) indexes the replicates

y_{ijkl} is a standardized VAS score of subject k assigned to pulse rate i and pulse width j in replicates l

μ is a reference level

α_i's are the main effects of pulse rate

β_j's are the main effects of pulse width

$(\alpha\beta)_{ij}$'s are the interaction between pulse rate and pulse width

B_k is the blocking factors of subject k

$\epsilon_{ijk} \sim N(0, \sigma_\epsilon^2)$

$B_k \sim N(0, \sigma_B^2)$

Table 3.6. DF in Equation 3.2

Source	DF
Pulse rate	2
Pulse width	2
Pulse rate * Pulse width	4
Subject	7
Error	128
Total	143

Before conducting ANOVA, two parametric assumptions were assessed in JMP® (SAS institute Inc., Cary, NC). Brown-Forsythe test was conducted to check for the equal variance, also known as homoscedasticity (Brown & Forsythe, 1974), and Shapiro-Wilk's test (Razali & Wah, 2011; Shapiro & Wilk, 1965) was utilized to check if the residual error has a normal distribution, also called normality. The results in Table 3.7 showed that data satisfied the assumptions of both homoscedasticity and normality of residuals for each motion.

Table 3.7. Results of homoscedasticity and normality tests for Study 1

Motions	Shapiro-Wilk Test (Normality)	Brown-Forsythe test (Homoscedasticity)
Grasping	W = 0.987313 p = 0.2113	$F_{8, 135} = 1.5047$ p = 0.1611
Opening	W = 0.989546 p = 0.3579	$F_{8, 135} = 0.8951$ p = 0.5226

Since the ANOVA assumptions were not violated, a 2-way ANOVA for each motion such as grasping and opening was conducted with one dependent variable, the standardized VAS scores.

3.2.8. Results

Table 3.8 shows the results of the raw VAS scores for the grasping and opening with nine combinations of two parameters, pulse rate and pulse width. The VAS scores shown in the table were sorted by parameters but the combinations of FES parameters were randomly applied to avoid potential order effects in the experiment. As shown in the table, the VAS scores varied not only from patient to patient due to the differences in subjective assessment, but also within the same patient because of the effects of the FES parameters. Thus, these raw VAS scores were standardized for each participant to control the variation between participants (Fischer & Milfont, 2010; Kane et al., 2005).

Table 3.8. Raw VAS score for flexion and extension

PR indicates pulse rate and PW implies pulse width. T1 and T2 represent the order of trials.

			S01		S02		S03		S04		S05		S06		S07		S08	
	PR	PW	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2	T1	T2
Grasping	30	180	43	37	13	3	63	33	29	56	50	51	35	21	74	60	82	81
	30	220	46	45	32	20	79	68	41	42	53	52	46	43	68	72	86	85
	30	260	61	51	12	26	41	83	67	63	52	50	42	58	67	81	76	81
	35	180	45	52	18	17	40	78	57	56	54	50	41	45	83	67	60	70
	35	220	41	54	35	28	39	59	66	67	54	50	35	30	85	74	69	78
	35	260	44	51	28	7	68	91	56	56	52	52	38	44	75	73	72	84
	40	180	43	55	6	34	40	41	42	46	50	51	46	37	61	59	89	89
	40	220	41	61	28	3	60	69	35	56	47	52	29	24	67	75	93	92
	40	260	44	45	26	22	57	39	57	66	49	50	20	38	80	64	79	88
Opening	30	180	4	51	7	10	89	60	61	57	0	19	39	14	49	75	74	61
	30	220	13	45	5	12	78	43	57	56	1	20	19	25	50	68	66	47
	30	260	81	46	11	2	39	51	45	54	17	15	26	19	80	56	58	59
	35	180	57	52	8	2	58	68	50	43	8	19	36	31	85	73	62	34
	35	220	29	51	6	4	70	70	62	56	10	19	39	37	69	65	81	75
	35	260	52	45	5	4	60	59	37	56	14	13	42	23	72	77	85	67
	40	180	63	52	10	6	77	41	44	44	37	21	29	10	64	68	55	54
	40	220	35	53	9	8	89	60	44	44	19	18	42	25	58	60	75	50
	40	260	55	54	10	7	69	39	56	56	18	30	18	17	59	63	44	43

The anthropometric information including the length of elbow-wrist and the circumference of the impaired forearm was recorded for each patient as shown in Table 3.9. The adequate X and Y coordinates of the cathode electrodes for the grasping and opening are also shown in Table 3.9 and 3.10. The coordinates of the anode electrodes were not analyzed as Lawrence (2009) found that the coordinates of anode electrodes were no significant effects on muscle contraction. The Y-coordinates in the tables represent the distance from the reference line, the X-axis defined in Section 3.2.5, to the cathode electrodes. Similarly, the X-coordinate is the distance from the middle (and thickest part) of the forearm, the Y-axis, where the medial direction is expressed as positive and the lateral direction as negative. The ratio of the Y-coordinate in the tables indicates the normalized distance to the length of elbow-wrist, while the ratio of the X-coordinate expresses the normalized distance to the circumference of the forearm.

The mean ratio values and standard deviations of the X- and Y-coordinates for each muscle group are also reported in Table 3.9 and 3.10. The mean ratio and standard deviation (STD) of the Y-coordinates for each muscle group (WF, FF, WE and FE) were 72.44 ± 3.34, 30.89 ± 3.22, 70.51 ± 3.33, and 29.08 ± 3.78, while that of the X-coordinates were -0.72 ± 9.11, -0.46 ± 3.32, 0.03 ± 5.07, and 0.26 ± 2.72, respectively. The results of the descriptive analysis showed that the adequate Y-coordinates of the cathode FES electrodes were relatively consistent between subjects compared to the X-coordinates. Even though the X-coordinates varied between patients, average cathode electrodes coordinates for all muscle groups were approximate to the middle line (zero at the X-axis).

Table 3.9. Coordinates and ratios of cathode electrodes for WF and FF

ID	Circumference of Forearm (cm)	Elbow-Wrist Length (cm)	Wrist Flexion				Finger Flexion			
			X-coordinate		Y-coordinate		X-coordinate		Y-coordinate	
			Position (cm)	Ratio (%)	Position	Ratio	Position	Ratio	Position	Ratio
S01	29.9	29.5	-1.2	-4.01	22.6	76.61	-1.6	-5.35	9.8	33.22
S02	29.7	29.4	-1.9	-6.40	20.7	70.41	0.7	2.36	8.4	28.57
S03	21.5	25.5	3.1	14.42	18.5	72.55	-0.2	-0.93	7.9	30.98
S04	27.4	27.5	-2.4	-8.76	19.4	70.55	-0.9	-3.28	8.9	32.36
S05	30.8	28.1	-0.9	-2.92	19.4	69.04	-0.9	-2.92	7.7	27.40
S06	26.7	26.5	-1.6	-5.99	18.1	68.30	1.0	3.75	7.1	26.79
S07	30.5	27.1	-2.2	-7.21	20.0	73.80	-0.5	-1.64	10.1	37.27
S08	23.1	23.9	3.5	15.15	18.7	78.24	1.0	4.33	7.3	30.54
			Mean	-0.72	Mean	72.44	Mean	-0.46	Mean	30.89
			STD	9.11	STD	3.34	STD	3.32	STD	3.22

Table 3.10. Coordinates and ratios of cathode electrodes for WE and FE

ID	Circumference of Forearm (cm)	Elbow-Wrist Length (cm)	Wrist Extension				Finger Extension			
			X-coordinate		Y-coordinate		X-coordinate		Y-coordinate	
			Position (cm)	Ratio (%)	Position	Ratio	Position	Ratio	Position	Ratio
S01	29.9	29.5	2.1	7.02	20.5	69.49	1.0	3.34	7.7	26.10
S02	29.7	29.4	-1.2	-4.04	19.8	67.35	-0.6	-2.02	7.0	23.81
S03	21.5	25.5	-1.2	-5.58	18.0	70.59	-0.6	-2.79	7.4	29.02
S04	27.4	27.5	0.9	3.28	19.8	72.00	-0.7	-2.55	7.9	28.73
S05	30.8	28.1	2.3	7.47	20.5	72.95	-0.7	-2.27	10.2	36.30
S06	26.7	26.5	0.3	1.12	16.9	63.77	0.8	3.00	6.8	25.66
S07	30.5	27.1	-1.3	-4.26	19.9	73.43	1.1	3.61	8.8	32.47
S08	23.1	23.9	-1.1	-4.76	17.8	74.48	0.4	1.73	7.3	30.54
			Mean	0.03	Mean	70.51	Mean	0.26	Mean	29.08
			STD	5.07	STD	3.33	STD	2.72	STD	3.78

The results of ANOVA are presented in Table 3.11 including the main and interaction effects. The table also includes partial eta squared (η^2) to measure the effect sizes, the proportions of the variability associated with an effect compared to the total variance, characterized by small, medium, and large effect with values of .01, .06, and .14, respectively (Cohen, 1988; Fritz, Morris, & Richler, 2012; Richardson, 2011).

Table 3.11. Results of ANOVA for the standardized VAS scores

		Grasping			Opening		
Source	DF	F-Value	*Pr* > F	Partial η^2	F-Value	*Pr* > F	Partial η^2
Model	15	1.1142	0.3503		1.0488	0.4108	
PR	2	2.068	0.1306	0.0313	1.1153	0.331	0.01713
PW	2	6.3879	0.0023*	0.09075	6.2748	0.0025**	0.08929
PR X PW	4	1.5134	0.2021	0.04516	2.9652	0.0221*	0.08481
Subject	7	0	1	0	0	1	0

** $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$*

The results showed that the means of the standardized VAS scores between the nine combinations of FES parameters were not significantly different for both grasping ($F_{15, 128}$ = 1.1142; p = 0.3503) and opening ($F_{15, 128}$ = 1.0488; p = 0.4108).

For the grasping motion, the main effect of PW was significant ($F_{2, 128}$ = 6.3879, p = 0.0023, η^2 = 0.09075) having a medium effect, and no other effects were significant. Tukey's Honest Significant Difference (HSD) test was chosen to determine significant differences in the main effects of PW because it has greater power while still controlling the familywise error rate than the other methods for controlling type 1 error (Myers, Well, & Lorch, 2010). The

results showed that the mean standardized VAS score of PW at 180 was significantly lower than that of others as shown in Figure 3.9.

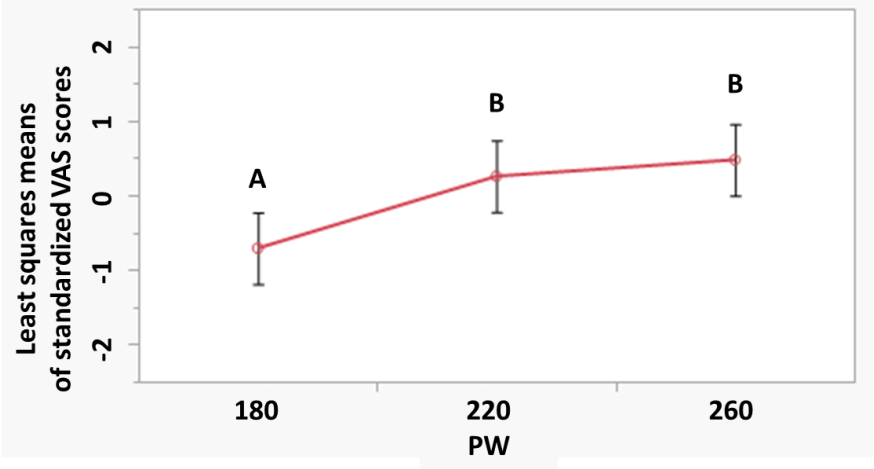


Figure 3.9. Differences in standardized VAS score for PW of grasping
Different letters above bars indicate a significant difference ($p < 0.05$)

Dunnett's test for the grasping motion with a control (PR = 35; PW = 220) was also performed to examine significant differences between the effects of fixed FES parameters and the user-specific parameters on perceived muscle pain and discomfort (Dunnett, 1955). Figure 3.10 illustrates the result of Dunnett's test, and the horizontal reference lines, UDL and LDL, represent 95% upper and lower decision limits, respectively. The results revealed that the standardized VAS score with FES parameters at 30/180 (PR/PW) was significantly lower than that of the control level at 35/220 (PR/PW).

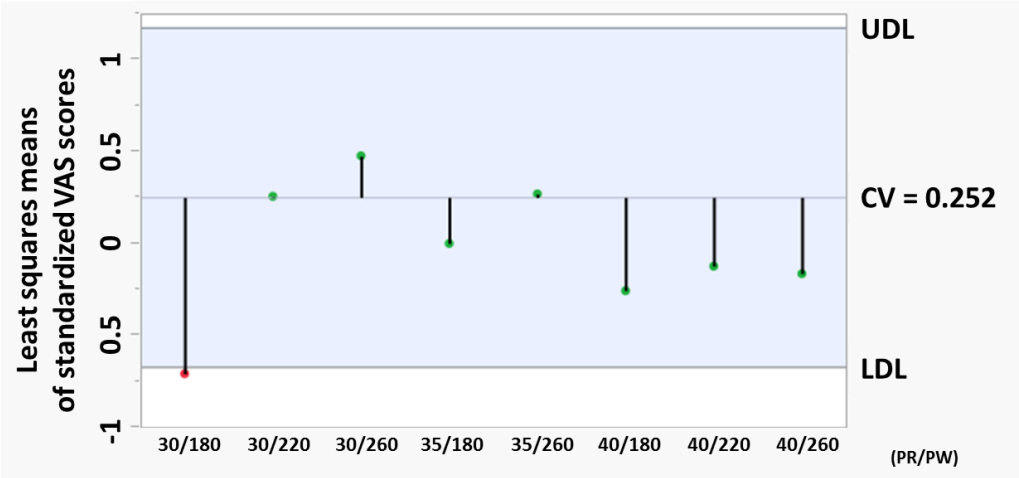


Figure 3.10. Control difference in standardized VAS score for PR/PW of grasping

UDL = Upper Decision Limit; LDL = Lower Decision Limit; CV = Control Value with PR/PW at 35/220

The results for the opening showed the main effect of PW ($F_{2, 128} = 6.2748$, $p = 0.0025$, $\eta^2 = 0.08929$) and interaction effect ($F_{2, 128} = 2.9652$, $p = 0.0221$, $\eta^2 = 0.08481$) were significant, and both effects had medium effect sizes. Figure 3.11 shows the interaction effect between PW and PR for opening.

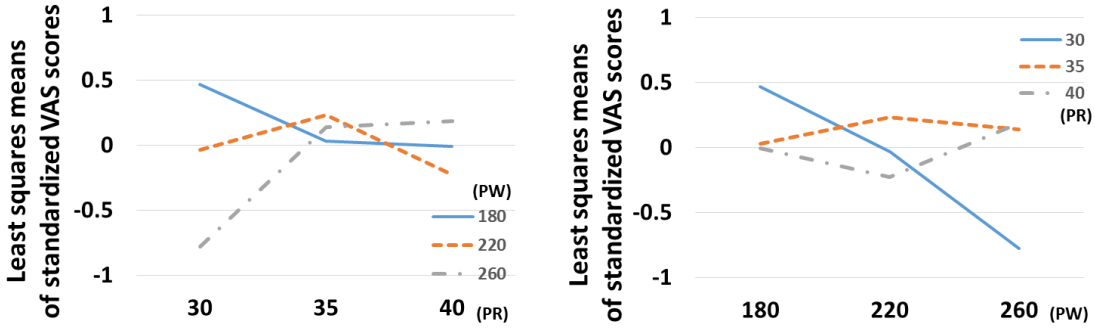


Figure 3.11. Interaction plots between PW and PR for opening

Similar to the grasping motion, Dunnett's test was performed to examine with a control (PR = 35; PW = 220) for the opening motion as shown in Figure 3.12. The results revealed that the standardized VAS score of FES parameters with PR/PW at 30/260 was significantly lower than that of the control level at 35/220 (PR/PW).

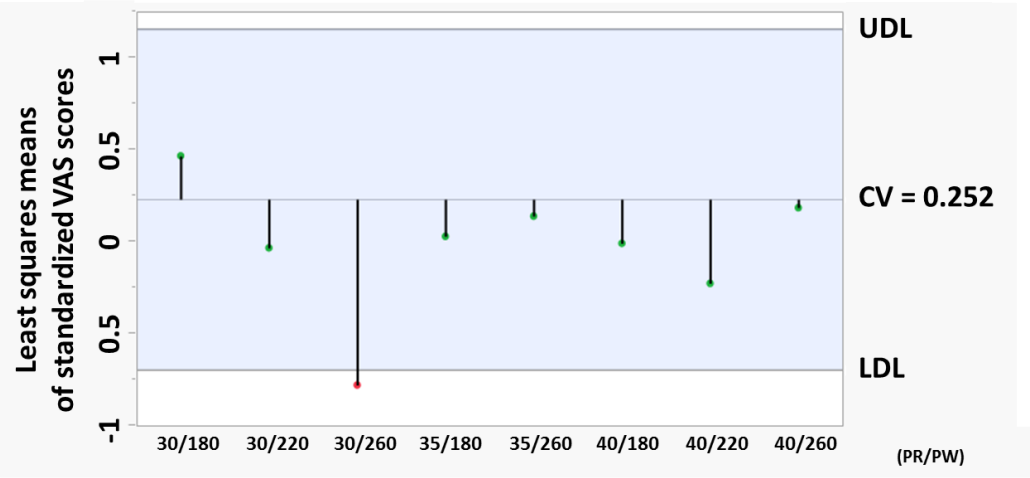


Figure 3.12. Control difference in standardized VAS score for PR/PW of opening
UDL = Upper Decision Limit; LDL = Lower Decision Limit; CV = Control Value with PR/PW at 35/220

Table 3.12 shows the selected FES parameters for PR and PW for each participant. As mentioned before, the user-specific FES parameters were determined by selecting the combination among the five lowest VAS scores which could open wide enough to be ready to hold a small ball and be strong enough strength to lift the ball properly.

Table 3.12. User-specific FES parameters for each patient

PR indicates pulse rate, and PW is pulse width

	Grasping		Opening	
ID	PR (Hz)	PW (μs)	PR (Hz)	PW (μs)
S01	30	220	30	180
S02	30	180	30	260
S03	40	260	40	260
S04	40	220	35	180
S05	40	220	30	220
S06	40	220	40	180
S07	30	260	30	260
S08	35	220	35	180

3.3. Discussion

In Phase 1, the FES system was built with four inexpensive, off-the-shelf TENS units. The developed FES system could support seven important features in FES operation identified in Section 2.1.4 and was also capable of controlling multiple FES electrodes to derive natural hand and wrist movements in real-time as summarized in Table 3.2.

In Phase 2, the adequate X and Y coordinates of the cathode electrodes for the grasping and opening were recorded, and the ratio of coordinates was calculated by normalizing the positions with respect to anthropometric data. The results indicated that the Y-coordinates of the cathode FES electrodes were relatively consistent between subjects compared to the X-coordinates, and the mean ratio values of the Y-coordinates for each muscle group (WF, FF, WE and FE) were 72.44 ± 3.34, 30.89 ± 3.22, 70.51 ± 3.33, and 29.08 ± 3.78, respectively. Even though the X-coordinates more varied between patients, the average cathode electrodes coordinates were approximate to the middle line of the forearm. These results could be utilized as an appropriate initial position with respect to anthropometric data for each muscle motion, such as WF, WE, FF, and FE. Moreover, the findings could address the lack of clear guidelines to determine FES electrode placement, and help novices without detailed knowledge of muscle anatomy to find adequate FES electrode placement.

The user-specific FES parameters were also determined by following the proposed systematic FES parameter setting procedure, and the statistical analyses were performed to investigate the effects of each combination of FES parameters on perceived muscle pain and discomfort. The results of ANOVA tests showed that the mean standardized VAS scores between all combinations of FES parameters were not significantly different for both grasping

($F_{15, 128}$ = 1.1142; p = 0.3503) and opening ($F_{15, 128}$ = 1.0488; p = 0.4108). However, the post-hoc analysis for the grasping motion revealed significant differences in the main effects of PW, and the results showed that the mean standardized VAS score of PW at 180 was significantly lower than that of others. Moreover, the results of Dunnett's tests for grasping and opening motions also indicated that the standardized VAS scores of some FES parameters were significantly lower than that of the control level at 35/220 (PR/PW). It implies that the application of user-specific parameters significantly decreases muscle pain and discomfort, and will, consequently, help to increase user satisfaction. Therefore, the null hypothesis of H1 was rejected in favor of the alternative hypothesis, which states that the application of the user-specific FES parameters significantly decreased perceived muscle pain and discomfort than that of the fixed FES parameters for both grasping and opening motions.

Furthermore, only one patient selected the control level as the user-specific FES parameter as shown in Table 3.12, and these results also supported the importance of the application of user-specific FES parameters. The user-specific FES parameter identified by the proposed procedure was utilized in the experiments in Study 2 with user-specific FES electrode placement.

In the post-experiment questionnaire, one participant mentioned some residual muscle fatigue, another showed a slight rash at the location where the electrode was attached, and a third person felt tingling on the forearm. However, all of them reported that the symptoms disappeared in a few hours at the follow-up survey. All of the participants responded with either "Very satisfied" or "Somewhat satisfied," and average overall satisfaction with Study 1 was 4.6 out of 5.0. One of the participants, who frequently used the similar TENS unit used in

this study, commented as follows, “The position of pads seems very important for (1) right physical action and (2) pain tolerance level,” and the patient was happy to know the adequate FES electrode positions and parameters.

During the experiment, one fact not included in the objectives of this study found that most subjects perceived more pain and discomfort when applying FES to the flexor muscle than extensor muscle. To validate this fact, the raw VAS scores of all subjects were divided into two groups such as grasping and opening, and Welch’s test was performed because the equal variance assumption was not satisfied based on the Brown-Forsythe test results ($F_{1, 286}$ = 7.1721; p = 0.0078). Welch’s test showed that mean VAS scores between two groups were significantly different ($F_{1, 278.95}$ = 15.2861; p = 0.0001). There are two possible reasons why the average VAS scores were different between motions. First, when the wrist extensor muscle is stimulated by FES, the fingers naturally assume a half-open position. The finger extension could be easily made by stimulating the finger extensor muscles. Contrarily, the wrist flexion has little effect on the finger flexion. Thus, most of the finger flexion should only be achieved through FES stimulation, and current amplitudes should be increased for enough grasping power, which could also increase perceived muscle pain and discomfort (Lawrence, 2009; Malešević et al., 2012). In addition, the FES electrodes of the finger flexion are generally located just above ulnar and median nerves as shown in Figure 2.1, unlike that of the finger extension, and these nerves are simultaneously stimulated when FES is applied which could cause perceived muscle pain and discomfort (Standring et al., 2008).

4. STUDY 2: DEVELOPMENT OF A NOVEL SMR-BASED BCI SYSTEM

4.1. Objectives

The objective of Study 2 was propose a novel SMR-based BCI with visual guidance to address the five main limitations of SMR-based BCI-controlled FES identified in the literature review in Section 2.3 as follows: (1) ambiguous instruction for MI tasks during training under SMR-based BCI systems; (2) lack of studies to classify different MI tasks in a single hand, such as grasping and opening; (3) difficulties in decoding voluntary and passive SMRs, and (4) inconsistent frequency band selection procedures to extract important SMR features.

In order to achieve the objective, participants were asked to follow a visual guideline consisting of video clips representing two different rhythmic MI tasks in synchronous BCI experiments to classify a 2-class MI task in a single hand. They were then asked to continue or stop the MI tasks when FES was activated to investigate the feasibility of distinguishing the existence of MI-induced SMRs.

After the synchronous BCI experiment, an offline analysis was conducted to determine a set of user-specific classification methods including; (1) the best classification algorithm, (2) the best set of classifier parameters, and (3) the best combination of frequency bands and EEG channels in terms of the classification accuracy. The results of Study 2 were then utilized for online BCI experiments in Study 3.

4.2. Methods

4.2.1. Participants

The same participants who did Study 1 were invited again on a separate day and were asked to conduct synchronous BCI experiments for MI training. Any patients who were displeased with FES and BCI experiments could cease at any time. However, no one chose to withdraw before the end of the study.

4.2.2. Visual Guideline

Since MI tasks do not involve physical movements, it is difficult for the experimenter to know whether the participant is performing MI tasks in the correct way. To address this issue, clear instructions are required to help participants during training. Thus, in this study, video clips were provided as a visual guideline for MI tasks, and participants were asked to follow the movie clips to train them in becoming familiar with the MI tasks.

The visual guideline consisted of two video clips to represent Slow One-time Grasping (SOG) and Fast Cyclic Opening (FCO), as shown in Figure 4.1. The video clip of SOG displayed a slow one-time grasping for three seconds (1/3 Hz) starting at a neutral position with a straight hand and wrist, while that of FCO showed a three-time repetition of opening motion (from a grasping position) for three seconds (1 Hz). Participants were then asked to imagine each motion depicted in the video clip as similar as possible. The two different rhythmic motions used in visual guidance were intended to classify a 2-class MI task in a single

hand utilizing distinct SMR features evoked by different rhythmic MIs (Choi et al., 2016; Gu et al., 2009).

These video clips were displayed on a 21-inch LCD monitor located approximately 42 inches in front of participants, and the centerline of the monitor was set within 10 degrees of eye level to follow the guideline of viewing distance and screen size, and viewing angle for individuals, respectively (Ahlstrom & Kudrick, 2007).

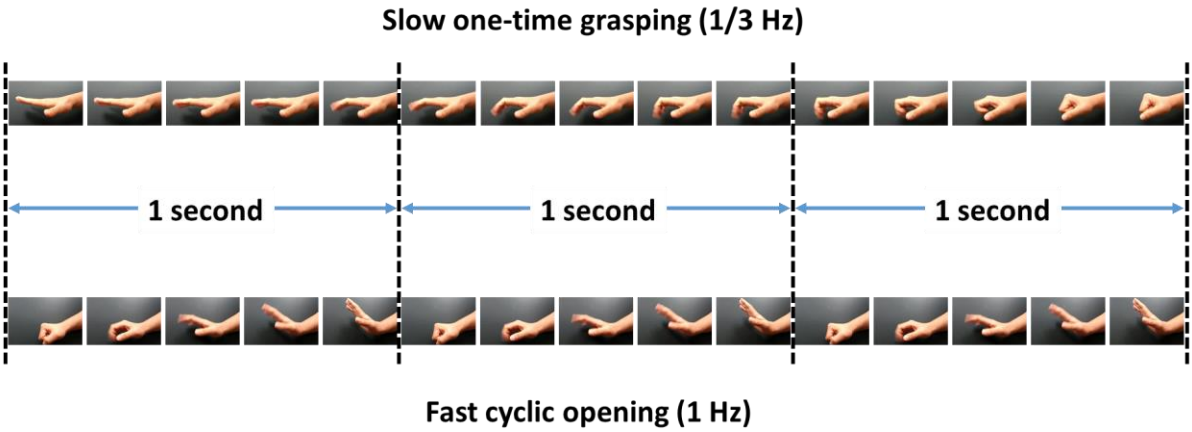


Figure 4.1. Visual guidance for grasping and opening motions

The upper images are for a slow one-time grasping and the lower images for a fast three-time opening.

4.3. Procedures

When participants returned, the skin preparation process was performed similar to Study 1 by following Axelgaard's guidelines (Axelgaard Manufacturing Co., Fallbrook, CA). FES electrodes were placed on the adequate coordinates with the user-specific FES parameters identified and recorded in Study 1. The anti-static wrist strap was then applied to the opposite hand of the affected forearm with the FES electrode to ground out the electrical stimulation.

Afterward, the participants were then asked to wear an EEG cap with 32 active EEG electrodes, and the gap between EEG electrodes and the scalp were filled with a conductive EEG gel to reduce impedance below 5 kΩ (g.tec medical engineering GmbH, Austria). When the FES and BCI systems were ready, participants were given detailed explanations of the synchronous experiment and were instructed on how to perform the MI tasks according to the visual guideline shown on the monitor.

The experiment in Study 2 consisted of five sessions with 24 trials per session, and there was a three-minute break between sessions. Each trial lasted 12 seconds and consisted of a rest period (2.5 seconds), a reference period with cues (2.5 second), an MI period (3 seconds), an FES initiation period (1 second), and a feedback period (3 seconds) as shown in Figure 4.2.

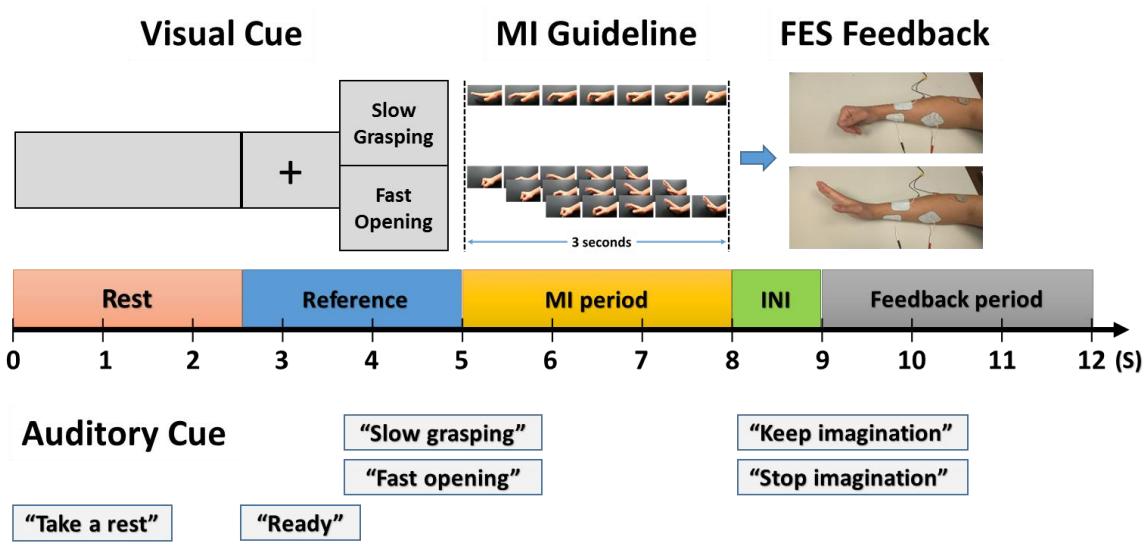


Figure 4.2. Structure of each trial

Text in the blue box indicates the auditory cue which played at the beginning of each period, and INI is an abbreviation of the FES initiation period.

During the rest period, the screen showed only the gray background without any image, and an auditory cue (“take a rest”) was played at the beginning of the rest period. Participants were required to remain calm during this period to stabilize EEG signals. The reference period was then followed by a cross fixation screen and an auditory cue ("ready") at the beginning of the period, and the visual (text) cue and the auditory cue for either "slow grasping" or "fast opening" were presented at the end of the reference period. The participants were asked to focus on the screen to be ready for MI tasks. Afterward, the MI period was successively given to participants with the visual guideline of SOG or CFO for three seconds. During this period, the participants were asked to mimic MI tasks as close as possible by following the visual cues. After the MI period, the FES initiation period lasted for 1 second, during which the FES system activated the same motion to the subjects’ affected forearm as presented in the visual guideline. In this period, the current amplitude of FES was gradually increased by utilizing the ramp time function to improve user satisfaction. At the end of the FES initiation period, the feedback period was successively given to the participants. In this period, the participants were required to keep or stop the MI tasks given in the feedback period according to auditory cues such as “keep imagination” or “stop imagination,” respectively.

In the MI period, participants conducted a total of 120 trials including 60 trials for each SOG and FCO, while they performed 60 trials for either keep or stop MI tasks in the feedback period. All trials were pseudo-randomized so that the number of trials for different conditions were balanced with each combination as shown in Table 4.1.

Table 4.1. The number of trials for each condition in Study 2

		Feedback Period		**Total**
		Keep	Stop	
MI Period	Grasping	30	30	60
	Opening	30	30	60
Total		60	60	120

The total time of the experiment was around 40 minutes, and the completion time of Study 2 was 60 minutes including the setup time. Figure 4.3 shows the structure of the experiment in Study 2.

Study 2	Experiment time	**41 min**	Total Trials	**120**

Session	**Session 1**								**Total (Min)**
Trial	Initial	Rest	Ref	MI	INI	FES	...	Trial 24	
Time (sec)	60	2.5	2.5	3	1	3	...	12	5.8

Break (3 minutes)

Session	**Session 2**								**Total (Min)**
Trial	Initial	Rest	Ref	MI	INI	FES	...	Trial 24	
Time (sec)	60	2.5	2.5	3	1	3	...	12	5.8

...

Session	**Session 5**								**Total (Min)**
Trial	Initial	Rest	Ref	MI	INI	FES	...	Trial 24	
Time (sec)	60	2.5	2.5	3	1	3	...	12	5.8

Figure 4.3. Structure of the experiment in Study 2

4.4. Signal Processing

EEG signals have some critical properties which should be considered including ‘noisy signal and outliers,’ ‘high dimensionality,’ ‘time information,’ and ‘non-stationarity’ (Lotte et al., 2007). Therefore, the brain signal should be carefully processed with consecutive steps to clean-up, extract, and identify relevant brain features. As described in Section 2.3.3, these steps include (1) signal acquisition; (2) signal preprocessing to filter out irrelevant information such as noise and artifacts; (3) feature extraction and selection to refine the brain features by extracting spatial and/or temporal information from the filtered signal, and (4) classification.

4.4.1. Signal Acquisition

The EEG signals were measured from 32 active electrodes (AFz, F7, F3, Fz, F4, F8, FC5, FC3, FC1, FC2, FC4, FC6, T7, C5, C3, Cz, C4, C6, T8, TP7, CP5, CP3, CPz, CP4, CP6, TP8, P3, P4, PO3, PO4, O1, and O2) with the ground at Fpz and the left earlobe reference as shown in Figure 4.4. The EEG signals were sampled at 256 Hz via two g.USBamp biosignal amplifiers (g.tec medical engineering GmbH, Austria), and notch-filtered at 60 Hz to remove electrical mains hum in the United States with the BCI2000 system (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004).

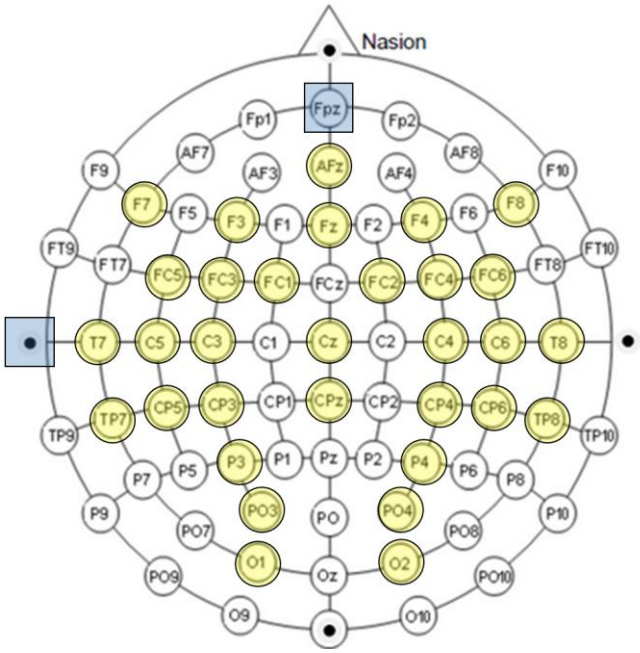


Figure 4.4. EEG electrode montage

The yellow circles indicate the selected 32 EEG channels, while the blue squares are for the ground electrode and the left earlobe reference

The recorded EEG signals were then divided into three subsets for further analysis as follows: (1) the reference and MI period for ERD/ERS and CSP analyses to detect the existence of MI-induced SMRs when FES was not being applied; (2) the MI period for the CSP method to classify a 2-class MI task in a single hand, and (3) the feedback period for the CSP analysis to decode the existence of SMRs when FES was being applied (See Figure 4.5).

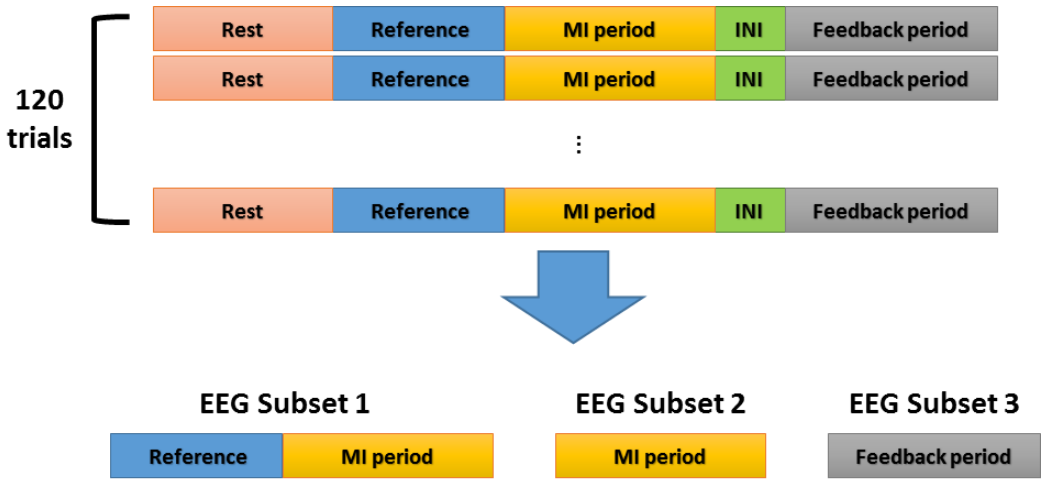


Figure 4.5. Structure of three subsets of the EEG signals in Study 2

4.4.2. Signal Preprocessing

Once the brain signals were recorded, noise, artifacts, and other irrelevant brain signals were filtered out. EEG signals were visually inspected for unexpected EEG contamination usually caused by body movements and electrode drifts during the experiments, and those trials were excluded from further processing. In addition, EEG signals were filtered by an automatic artifact rejection toolbox from the EEGLAB v13.6.5b (Delorme et al., 2001; Delorme & Makeig, 2004; Nolan et al., 2010). The rejection thresholds were set at 150 μV for the large fluctuation threshold and 3 STD for the probability threshold of entropy and kurtosis. The remaining trials were then band-pass filtered between 1-29 Hz to remove irrelevant brain signals such as muscle artifacts. Figure 4.6 shows the examples of the rejected trials due to the electrode drift and physical movement detected from the automatic artifact rejection toolbox in EEGLAB.

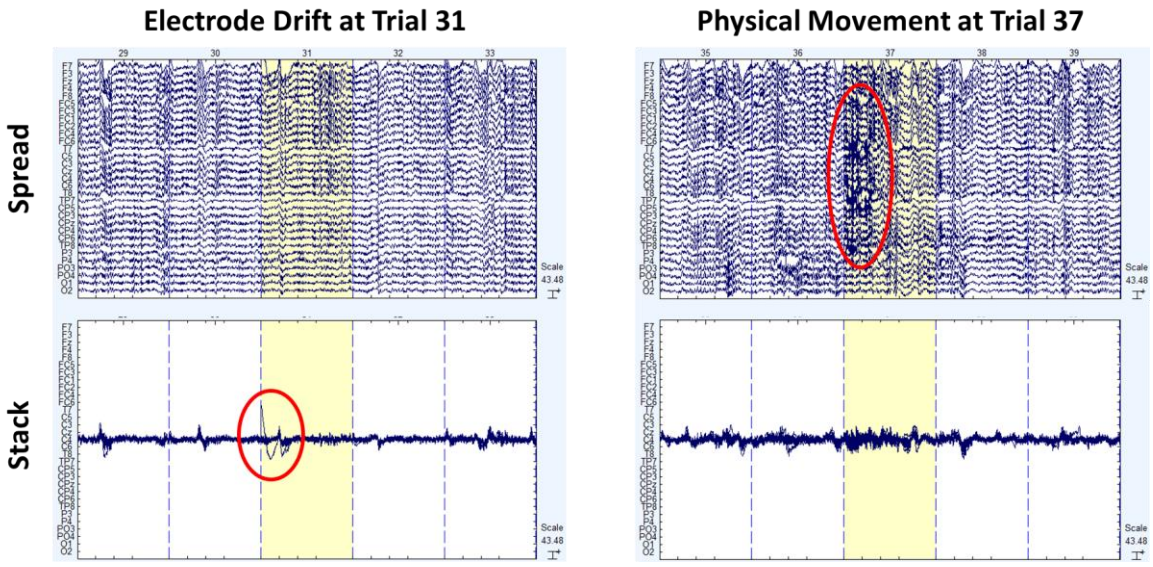


Figure 4.6. Examples of the rejected trials

The left figure shows EEG signals with electrode drifts at 31st trial, and the right figure displays EEG signals with physical movements at 37th trial. The upper plots illustrate the spread EEG signals for each channel, while the lower plots show the stack EEG signals. The red circles indicate the abnormal signals, and yellow-colored background depicts the rejected trials.

Afterward, PCA was applied to the filtered EEG signals to project high dimensional data (32 channels) into lower dimensions while maintaining important brain features. After applying PCA, eigenvectors and eigenvalues of a covariance matrix were generated. Among all eigenvalues, the first few components which could explain 95% of variance were selected with the assumption that the important brain features are contained in those few components. The retained principal components were then projected back with the reduced dimensional EEG signal by excluding unimportant components. This procedure not only addresses the high dimensionality issue but also helps to speed up an ICA decomposition process by reducing the dimension of the EEG signal.

The reduced dimensional EEG signals after the PCA procedure still mixed with irrelevant independent components such as eye-blinking artifacts and visual stimulus-evoked

potentials. Thus, an ICA method was applied to retain only the relevant independent components by removing irrelevant components. After the ICA decomposition process, the EEG signals were decomposed into maximally independent components, and the artifact (irrelevant) components could be identified by plotting each independent component in a component activity time course and a topographical map. After removing the artifact related components, EEG signals were projected back with the whitened data.

Figure 4.7 illustrates the examples of ICA components that should be rejected. The figures on the left in Figure 4.7 display the scalp topographical map, while the right plots show the component activity time course of the relative strength over the trials. The X-axis of the time course represents the elapsed time from the beginning of the MI period (± 3 seconds), while the Y-axis shows the trial sequence numbers. The red vertical lines in the right figures indicate the timing when the visual cues, such as the cross fixation, “slow grasping” text, and “fast opening” text, were given to participants. The scalp topographical map in Figure 4.7 (a) shows that the eye-blinking artifacts occurred mainly near the forehead (AFz), and the eye-blinking artifacts are represented as blue spots in the component activity time course. In contrast, the visual stimulus-evoked potentials occurred near the occipital cortex as shown in Figure 4.7 (b), and the time course plot indicates that ERPs evoked by visual stimulus occurred around 300ms after the visual cues were given. Figure 4.7 (c) depicts the electrode drift noise at FC6, and the time course plot shows that there were strong line noises near 100th trial and 115th trial. As mentioned previously, these independent components were not related to SMRs evoked by MIs, so they were removed from the EEG signals for further analysis.

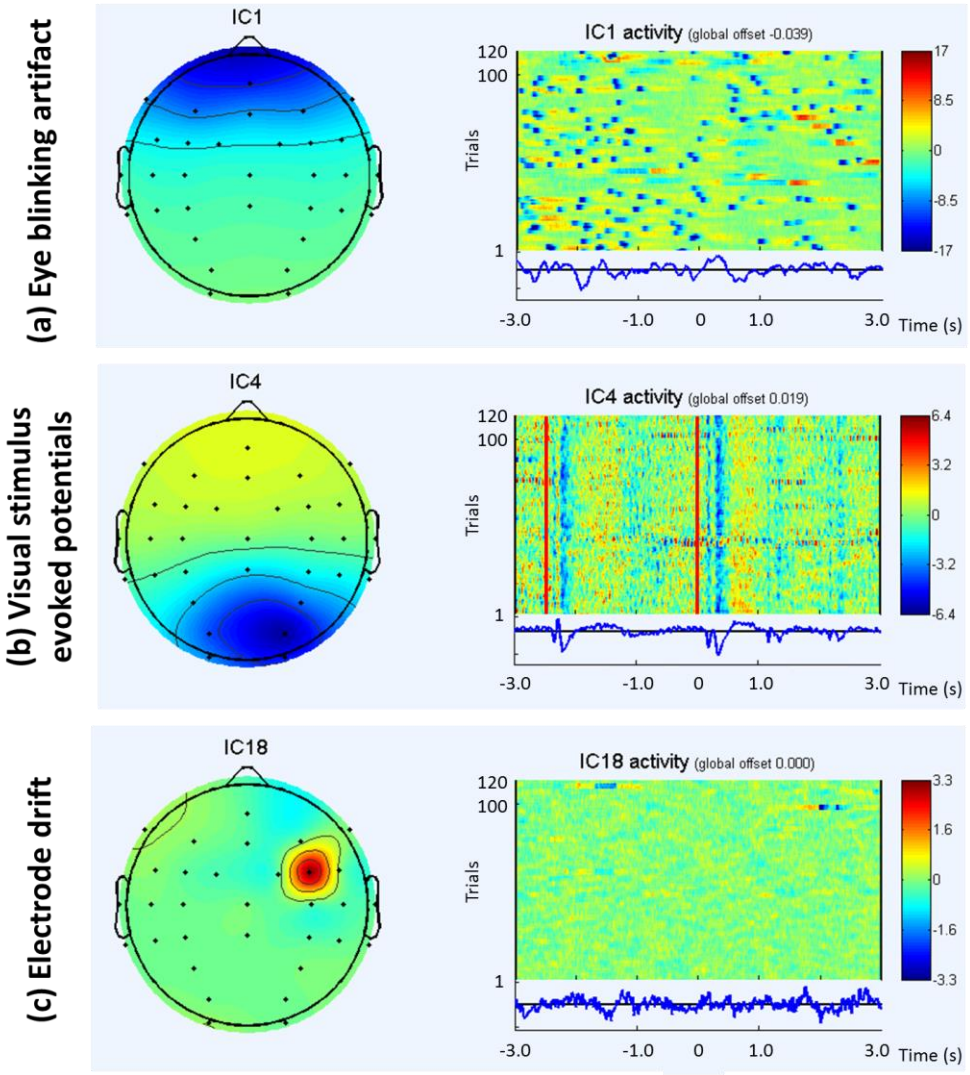


Figure 4.7. Examples of the rejected ICA components from Subject 'S06'

(a) The component of eye-blinking artifacts, (b) that of the visual stimulus-evoked potentials, and (c) that of the electrode drifts. The X-axis of the right figures represents the elapsed time (s), the Y-axis shows the trial, and red vertical lines indicate when the visual cues were given.

Finally, the surface Laplacian estimation was applied to the EEG signals between the reference and MI periods to enhance spatial EEG traces of the ERD/ERS procedure (McFarland et al., 2000; Schalk & Mellinger, 2010). The ranges of surface Laplacian were set as 0.15 and 0.27 (lower and upper bound in distance ratios, respectively) to determine the distance limits for determination of $V_{(j)}$ in Equation 2.1. With the set of limit ratios, the electrodes near $V_{(i)}$ with distance ratios of adjacent electrodes of 0.15 and 0.27 were selected as the $V_{(j)}$'s. Table 4.2 shows the selected adjacent electrodes, $V_{(j)}$'s, corresponding to the target electrode, $V_{(i)}$ for the surface Laplacian estimation.

Table 4.2. The selected adjacent electrodes for surface Laplacian

V(i) indicates the target electrode, and V(j)'s are the selected adjacent electrodes with respect to the target electrode.

$V_{(i)}$	$V_{(j)}$'s
AFz	F3, F4, FC1, FC2
F7	F3, FC3, T7, C5, C3
F3	AFz, F7, Fz, FC5, C5, C3
Fz	F3, F4, FC3, FC4, Cz
F4	AFz, Fz, F8, FC6, C4, C6
F8	F4, FC4, C4, C6, T8
FC5	F3, FC1, T7, TP7, CP5, CP3
FC3	F7, Fz, T7, C5, Cz, CP5, CP3
FC1	AFz, FC5, FC2, C5, C3, CP3, CPz
FC2	AFz, FC1, FC6, C4, C6, CPz, CP4
FC4	Fz, F8, Cz, C6, T8, CP4, CP6
FC6	F4, FC2, T8, CP4, CP6, TP8
T7	F7, FC5, FC3, C3, CP5, CP3
C5	F7, F3, FC3, FC1, CP3, P3
C3	F7, F3, FC1, T7, Cz, TP7, CPz, P3
Cz	Fz, FC3, FC4, C3, C4, CP3, CP4
C4	F4, F8, FC2, Cz, T8, CPz, TP8, P4
C6	F4, F8, FC2, FC4, CP4, P4

T8	F8, FC4, FC6, C4, CP4, CP6
TP7	FC5, C3, CP3, P3
CP5	FC5, FC3, T7, P3, Po3
CP3	FC5, FC3, FC1, T7, C5, Cz, TP7, CPz, PO3
CPz	FC1, FC2, C3, C4, CP3, CP4, P3, P4, PO3, PO4
CP4	FC2, FC4, FC6, Cz, C6, T8, CPz, TP8, PO4
CP6	FC4, FC6, T8, P4, PO4
TP8	FC6, C4, CP4, P4
P3	C5, C3, TP7, CP5, CPz, O1
P4	C4, C6, CPz, CP6, TP8, O2
PO3	CP5, CP3, CPz, PO4, O2
PO4	CPz, CP4, CP6, PO3, O1
O1	P3, PO4, O2
O2	P4, PO3, O1

Figure 4.8 shows the summary of the signal preprocessing for the EEG subsets.

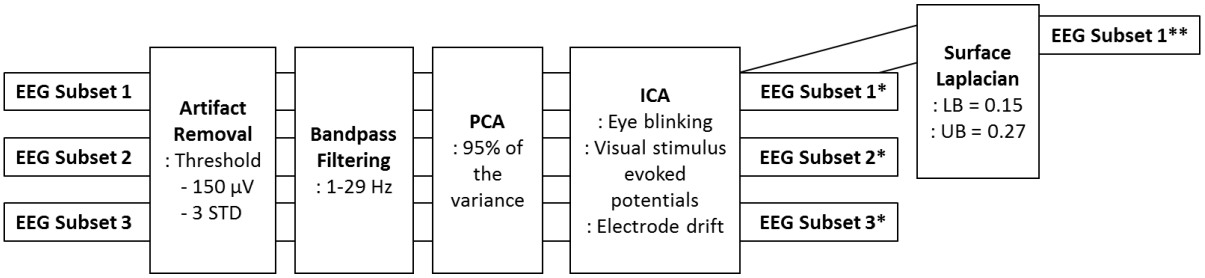


Figure 4.8. Summary of the signal preprocessing for the EEG subsets

4.4.3. Feature Extraction

After the signal preprocessing procedure, two feature extraction methods were utilized including ERD/ERS (Pfurtscheller & Neuper, 2006; Young et al., 2015) and CSP methods (Golub et al., 2016). The ERD/ERS method was applied only to the one subset (EEG subset 1**), while the CSP was analyzed for the other EEG subsets (EEG subsets 1*, 2*, and 3*).

To compute ERD/ERS, the preprocessed EEG subset 1** including both SMR and reference periods were band-pass filtered with a width of 4 Hz by FIR filter (Daly et al., 2009; Novi et al., 2007). The EEG signals were then divided into seven sub-bands from the first sub-band bin, [1-5) Hz, to the seventh sub-band bin, [25-29) Hz, with 4 Hz intervals. Afterward, the EEG data of each sub-band bin were transformed from time-domain data to frequency-domain data by using FFT with the Hamming windowing method for 2.5-second data epoch (640 data points). Afterward, the relative band power of each sub-band bin, ERD/ERS, was computed with the value of FFT in the reference period and that in the MI period for each trial by following Equation 2.2 (Pfurtscheller & Lopes, 1999).

The other three EEG subsets were analyzed with the SBCSP which can project a multidimensional EEG dataset into a low-dimensional subspace as described in Section 2.3.3.3. To decompose the EEG subsets into multiple sub frequency bands, the EEG signals were band-pass filtered for seven frequency bins by following the same procedure utilized in the ERD/ERS method. From each sub-band bin, the eigenvalues were calculated and utilized to determine the best feature from the projected EEG matrix (Pfurtscheller, Linortner, Winkler, Korisek, & Müller-Putz, 2009). The features from SBCSP then utilized to increase the subsequent classification accuracy by fusing the classification scores of each sub-band feature.

Figure 4.9 shows the summary of the feature extraction procedure for all EEG subsets.

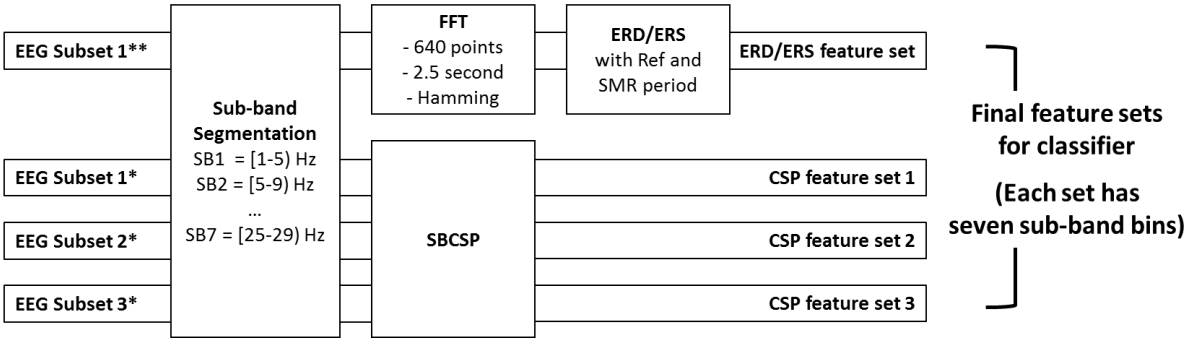


Figure 4.9. Summary of the feature extraction procedure for all EEG subsets

4.4.4. Classification

In this study, three different classification algorithms, Fisher's LDA, SVM, and ensemble methods were tested to identify the best classification algorithm and classifier parameters. Many BCI studies have reported good classification outcomes with LDA and SVM (Bhattacharyya, Konar, & Tibarewala, 2014; Kamrunnahar, Dias, & Schiff, 2009; Lee & Choi, 2003; Schlögl, Lee, Bischof, & Pfurtscheller, 2005), as well as have validated these methods as among the most suitable algorithms for SMR feature classification (Bashashati et al., 2007; Lotte et al., 2007). For the SVM classification algorithm, the kernel function used quadratic components to cover non-linear characteristics in the brain signal, and the least-squares method was applied to find the separating hyperplane. The ensemble method by combining the outputs of the LDA and SVM classifiers was also evaluated to test hypothesis 2.3, and the final decision

of the ensemble method was made with the weighted majority voting by combining the decisions of LDA and SVM, as well as by combining the features of each classifier as described in Section 2.3.3 (Polikar, 2006).

Each EEG subset was uniformly divided into 10 sub-datasets to apply a 10-fold cross-validation method (Kohavi & others, 1995). Nine sub-datasets were used as training datasets to build a classification weight vector, and the remaining one sub-date set was utilized as a test dataset to calculate the classification accuracy.

Figure 4.10 shows the summary of the classification procedure.

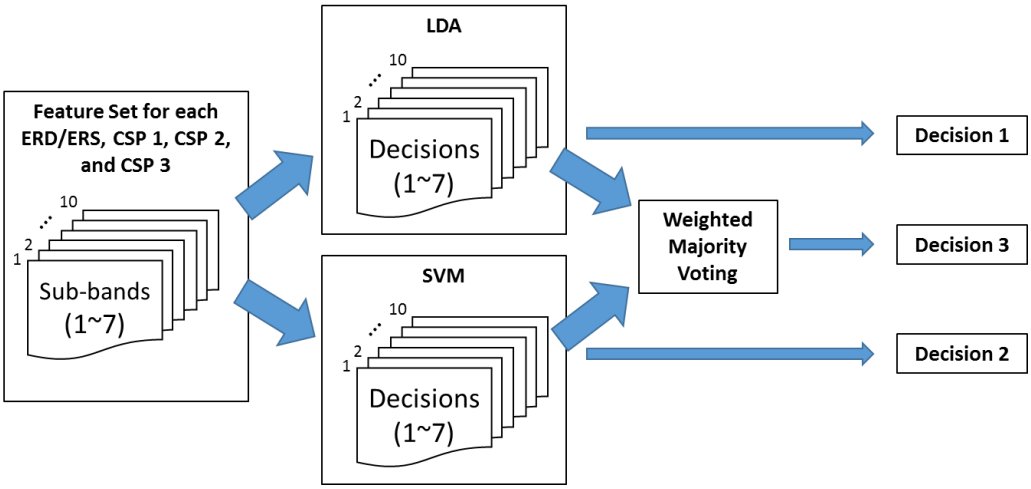


Figure 4.10. Summary of the classification procedure

4.5. Independent Variables

In the experiment, two IVs were manipulated including a period type and a classification type. The period type had three levels including SMR, ACT, and FES periods, and each period had different roles as follows; (1) detecting the existence of MI-induced SMRs when FES was not being applied; (2) classifying a 2-class MI task in a single hand, and (3) decoding the existence of SMRs to control FES when FES was being applied. The classification type had three levels for all periods such as LDA, SVM, and ensemble methods. The summary of IVs is shown in Table 4.3.

Table 4.3. Summary of IVs

IV	Level		
Period Type	SMR period (To detect SMRs without FES)	ACT period (To classify a 2-class MI task)	FES period (To decode SMRs with FES)
Classification Type	LDA	SVM	Ensemble

4.6. Dependent Variables

Three DVs were measured including task performance, brain activity, and subjective assessment. First, brain activity was analyzed to identify the SMR features including topographies, component activity time courses, and relative band power of brain signals. Task performance was statistically analyzed to test the hypotheses set in Section 2.4.2. The subjective mental workload was measured as the subjective assessment, and it was analyzed in Study 3 with the result of Study 3.

4.6.1. Brain Activity

The brain activity analysis was to validate and identify the SMR-related brain features with topographies, component activity time courses, and relative band power of brain signals.

4.6.2. Task Performance

Accuracy (%)

Accuracy in this experiment indicates the ratio of the correct classifications over the number of trials (Nam et al., 2015). The results from 10-fold cross-validation for each period were averaged to calculate the accuracy with three classification types (Kohavi & others, 1995).

4.6.3. Subjective Assessment

NASA Task Load Index (NASA-TLX)

After the experiment had been completed, the participants were asked to answer the NASA-TLX questionnaire (See Appendix F) to measure the subjective mental workload (Hart & Staveland, 1988). However, the result was not analyzed in Study 2, but it was analyzed in Study 3 by comparing changes in the subjective mental workload between two experiments for each subject. Participants were also asked to complete a post-experiment questionnaire (See Appendix E). The results of the survey were discussed in the following section.

Survey

Participants were asked to complete the post-experiment questionnaire (See Appendix E) after the experiment. The questionnaires of the survey included overall satisfaction of the experiment, personal opinions and suggestions for future research studies.

4.7. Experiment Design and Statistical Analysis

The objectives of the statistical analysis were to investigate (1) the feasibility of classifying a 2-class MI task in a single hand; (2) the feasibility of detecting the existence of MI-induced SMRs when FES was activated, and (3) the effect of different classification methods. From the results, hypotheses H2.1 to H2.3 were tested.

Since the experiment in Study 2 was a balanced 3 x 3 within-subjects factorial design with two IVs (the period type and classification type) with participant as a blocking variable and one DV (accuracy), a univariate ANOVA was set to analyze the main effects of two IVs and the interaction effect between IVs. Equation 4.1 and Table 4.4 show the experimental model and DF of the model, respectively.

Equation 4.1. Experimental model for Study 2

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \mathrm{B}_k + \varepsilon_{ijk}$$

Where

i = 1, 2, and 3 indexes the level of the period type

j = 1, 2, and 3 indexes the level of the classification type

y_{ijk} is the averaged accuracy of subject k assigned to task i with classifier j

μ is a reference level

α_i's are the main effects of the period type

β_j's are the main effects of the classification type

$(\alpha\beta)_{ij}$'s are the interaction between the period type & the classification type

B_k is the blocking factors of subject k

$\epsilon_{ijk} \sim \mathrm{N}(0, \sigma_\epsilon^2)$

$\mathrm{B}_k \sim \mathrm{N}(0, \sigma_B^2)$

Table 4.4. DF in Equation 4.1

Source	DF
Period Type	2
Classification Type	2
Period Type * Classification Type	4
Subject	7
Error	56
Total	71

Before conducting ANOVA, two parametric assumptions were assessed in JMP® (SAS institute Inc., Cary, NC), similar to Study 1. The results in Table 4.5 showed that data satisfied the assumptions of both homoscedasticity and normality of residuals. Since the ANOVA

assumptions were not violated, a 2-way ANOVA was conducted with one dependent variable, the accuracy.

Table 4.5. Results of homoscedasticity and normality tests for Study 2

Shapiro-Wilk Test (Normality)	Brown-Forsythe test (Homoscedasticity)
W =0.982593 p = 0.4207	$F_{8, 54}$ = 0.7150 p = 0.6773

4.8. Results

4.8.1. Brain Activity

After the experiment, brain activity of each subject was analyzed to identify the SMR-related brain features. Once brain signals were recorded during the signal acquisition process, the EEG data were filtered out in the preprocessing stage. Most of the signal preprocessing steps could be automated, such as the automatic artifact rejection and the band-pass filtering procedures, but the ICA procedure required visual inspections to determine which independent components were relevant SMR features. Figure 4.11 shows the independent components of subject 'S04' during the reference and SMR periods. The independent components were derived from the ICA procedure after reducing the dimension from 32 channels to 18 channels by the PCA procedure. The components marked in red indicate rejected components, while the blue components represent the ones to be used for further analysis.

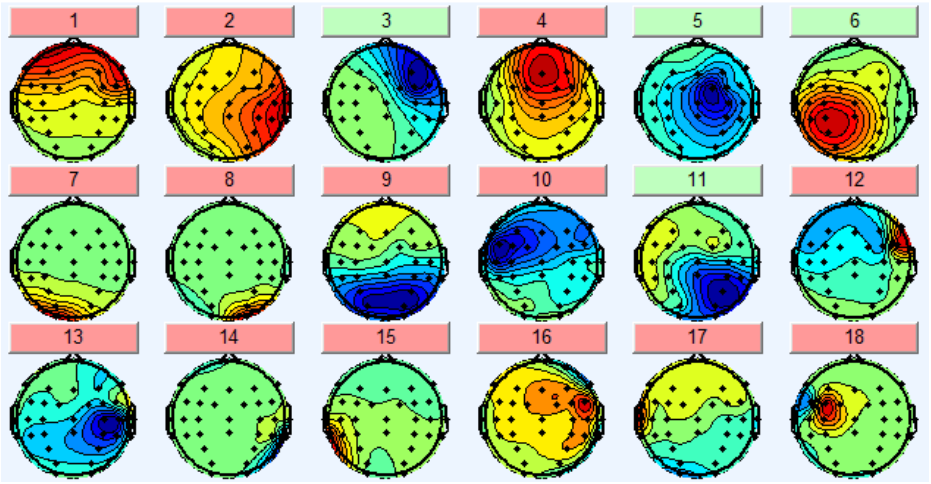
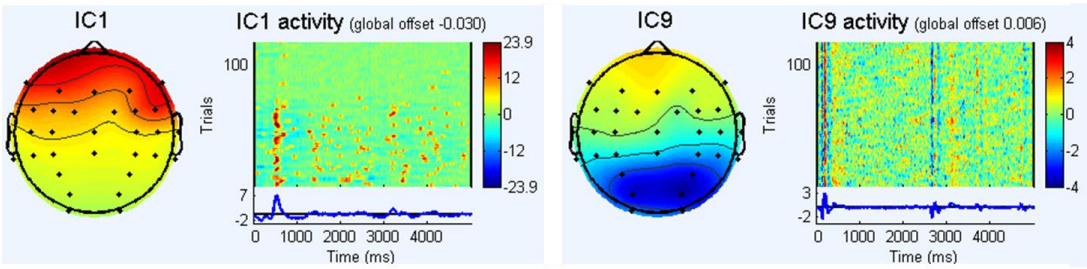


Figure 4.11. Scalp topographies of subject 'S04'

The criteria to reject independent components were eye-blinking artifacts which mainly occurred near the forehead and visual stimulus-evoked potentials occurring near the occipital cortex. The eye-blinking artifacts are usually short, but with high power, so point-like noises appear randomly, as shown in Figure 4.12 (a), whereas the visual stimulus-evoked potentials appear at the same time between trials as blue vertical lines as shown in Figure 4.12 (b). Furthermore, movement-related artifacts occurred near the temporal cortex areas (14th and 15th components in Figure 4.11), and electrode drift-related noises were also removed (13th and 18th components in Figure 4.11).



(a) **(b)**

Figure 4.12. Component activity time course for rejected components

The X-axis represents time (ms), and the Y-axis indicates trials

Figure 4.13 shows ERP plots before and after the signal preprocessing procedure for each EEG channel. The red plot of the pop-up graph represents the signal before the noise removal procedure, whereas the blue plot indicates the signal after the noise removal procedure. The black vertical line at 0-second indicates the time when the cross fixation was displayed, a green dash-dotted line refers the time when the auditory cue, "ready," was given, and an orange dotted line indicates the time when visual cues were given. From the results shown in the plot, it confirmed that the signal preprocessing procedure could successfully remove the irrelevant signals.

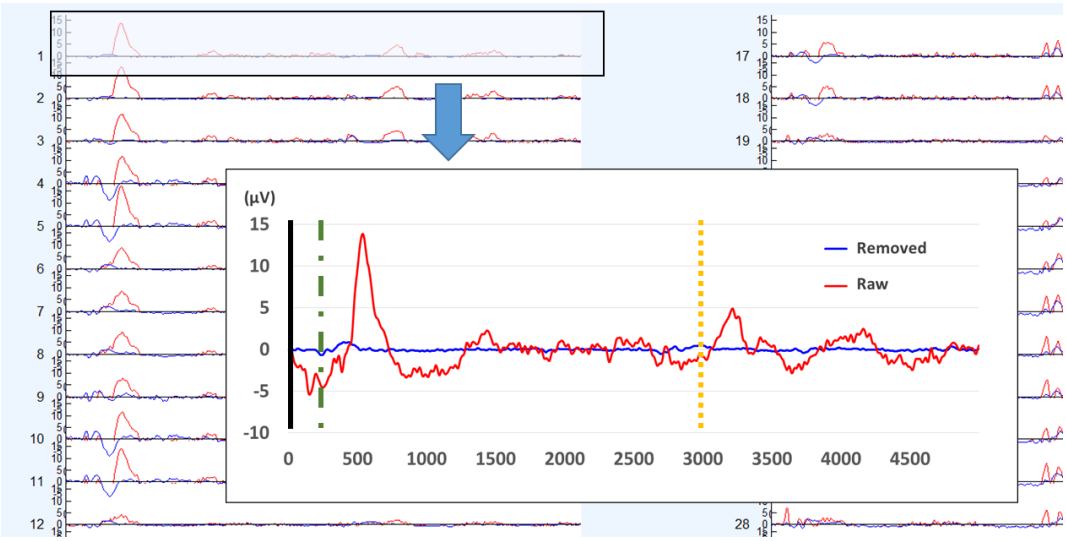
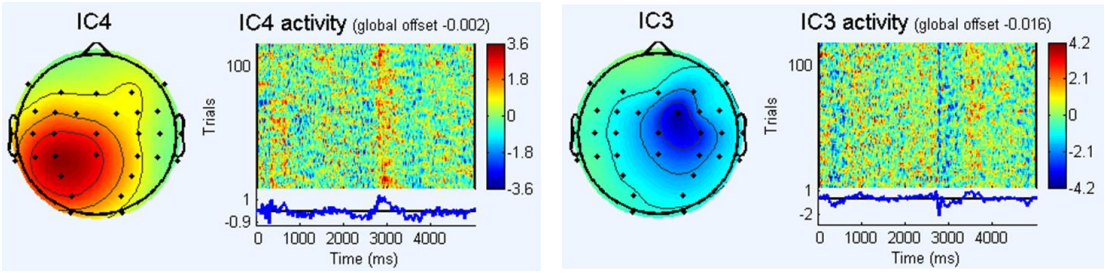


Figure 4.13. ERP plots before and after the artifact removal procedure

The X-axis represents time (ms), and the Y-axis indicates spectral power. The black vertical line at 0-second indicates when the cross fixation was displayed, the green dash-dotted line for the onset of the auditory cue, "ready," and the orange dotted line for the onset of visual cues.

After artifact removal process, the scalp topographies of remaining independent components were used to identify SMR-related features evoked by MI tasks. Figure 4.14 indicates two selected independent components from subject ‘S04’ who suffered from left

hemiparesis. In the component activity time courses, MI tasks were initiated at 2500 ms. The results showed that Power Spectral Density (PSD) of the ipsilateral motor cortex increased, while that of the contralateral motor cortex decreased immediately after the onset of MI. This result is similar to the ERD/ERS patterns confirmed in the literature review (Blankertz et al., 2007; Müller et al., 2003). Furthermore, it can be seen that the brain signal patterns before and after the point when the MI task started are very different from each other. These distinctive patterns are very important features that allow the classifier to distinguish the presence of MIs.



(a) **(b)**

Figure 4.14. Component activity time course for selected components of subject 'S04'

The X-axis represents time (ms), and the Y-axis indicates spectral power. MI tasks were initiated at 2500 ms.

One participant, however, identified as subject 'S01', who showed bad performance did not have the above distinguishing brain features. Figure 4.15 represents all independent components after reducing to nine dimensions by PCA procedures, and only three components remained after removing irrelevant components. Unlike the results of the good performer, there was no specific pattern that could distinguish between before and after the reference and SMR periods based on the MI initiated point of 2500 ms. As a result, the classification accuracy of this participant was low will be subsequently shown.

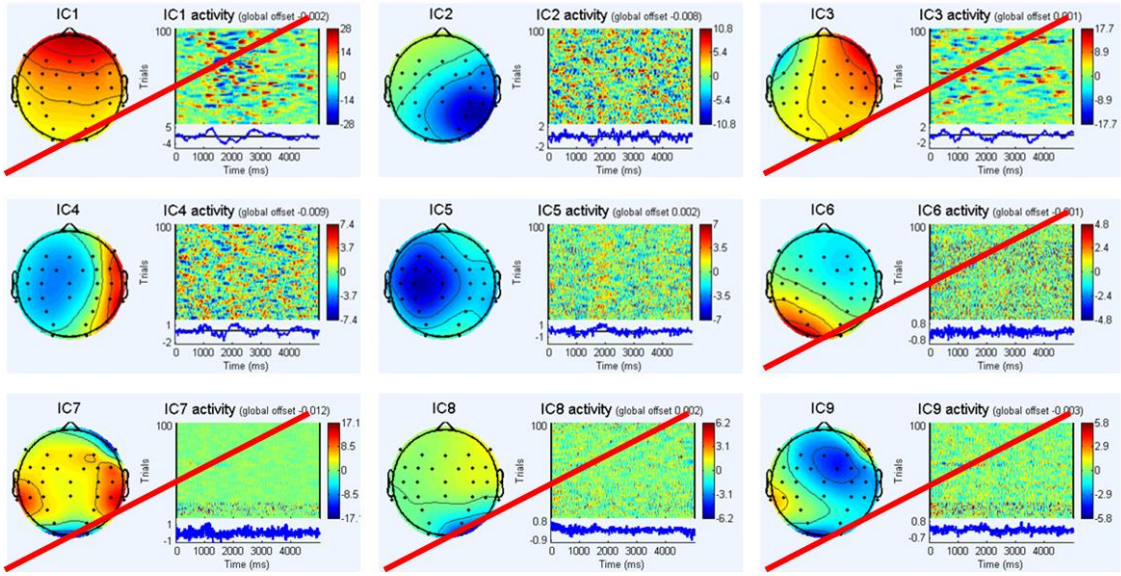
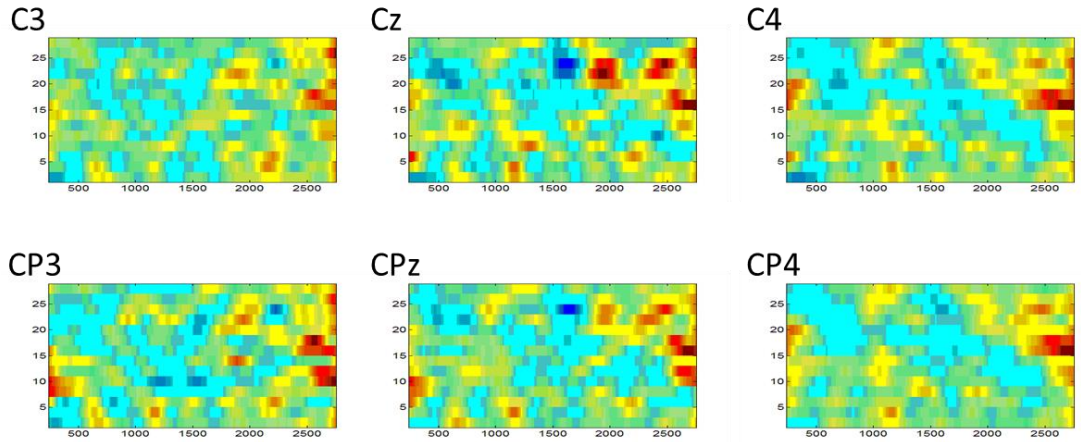


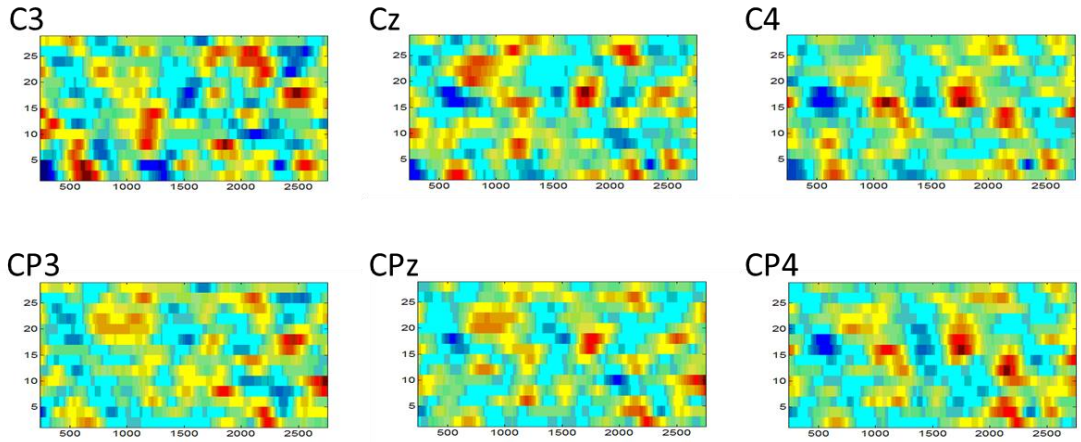
Figure 4.15. All independent components of subject 'S01'

Red oblique lines indicate the components were removed.

Brain activity during the ACT period was also evaluated to identify the features elicited by the 2-class MI task in a single hand such as SOG and FCO. As defined previously, the MI task of SOG was slow one-time grasping imagination, while that of FCO was fast three-time opening. The reason for applying different speeds and frequencies of MI tasks to this experiment was to validate that the 2-class MI task can be distinguished by deriving MI features with different characteristics. Using data from subject 'S06' who suffers from right hemiparesis, an Event-Related Spectral Perturbation (ERSP) analysis was performed for each MI task by the EEGLAB toolbox (Delorme et al., 2001; Delorme & Makeig, 2004; Nolan et al., 2010) as shown in Figure 4.16. In this figure, the X-axis represents the time from the MI starting point and the Y-axis the frequency from 1-29Hz similar to the time-frequency analysis. The color scale, however, implies a change in spectral power from the MI starting point, not the absolute spectral power.



(a)



(b)

Figure 4.16. ERSPs from subject 'S06' (right hemiparesis) during the ACT period

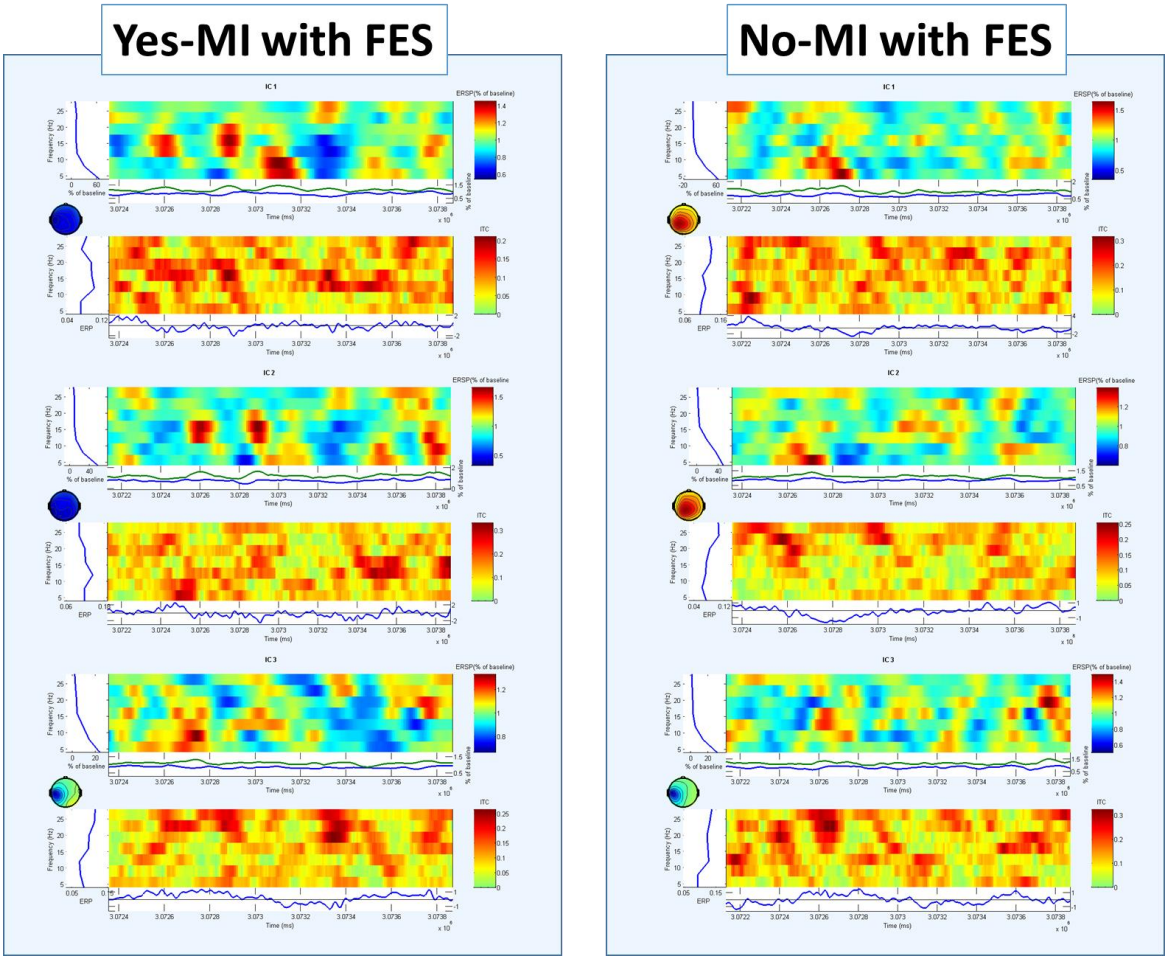
(a) Six EEG channels near motor cortex for SOG, and (b) channels for FCO. The X-axis represents the time (ms) from when the MI task was started, while the Y-axis indicates the frequency from 1-29Hz. The color scale implies the relative PSD from the MI starting point.

The reason for choosing the ERSP analysis was that there are several advantages compared to other analysis methods. First, compared with the ERD / ERS method, it is possible to analyze various bands without having to set a specific frequency band such as α- and β-bands. Moreover, unlike the time-frequency analysis, which indicates absolute spectral power, the ERSP method showed the relative spectral power based on the pre-defined baseline (e.g.

MI starting point), so that the EEG changes after the occurrence of the event can be easily identified.

The results showed that brain activity induced by FCO-MI was more dynamic than that induced by SOG during the ACT period. In Figure 4.16 (a), one ERD is seen the beginning of the MI task, and one ERS at the end of the MI task near the beta band. On the other hand, the results of FCO showed that ERD and ERS occurred alternately as shown in Figure 4.16 (b). This repetitive appearance coincides with the timing when FCO was repeated three times for 3 seconds, and confirms that the repeated MI tasks induced SMRs with repetitive patterns. In particular, comparing the C3 channels of both figures makes it possible to see the difference more clearly, because the participant suffers from right hemiparesis.

The FES period was also analyzed to identify the distinct features. Figure 4.17 shows three independent components near the motor cortex for each condition including with and without MI tasks when FES was activated. As shown in Figure 4.17, little more active patterns were found in Figure 4.17 (a) which could be utilized to classify two conditions. However, FES noise and FES-driven passive-movement-evoked SMRs were mixed with voluntary MI-evoked SMRs, making it difficult to find relevant components after ICA in most participants' results.



(a) **(b)**

Figure 4.17. ERSPs of ICA components from subject 'S07' during the FES period

(a) Three independent components near motor cortex for yes-MI under FES, and (b) components for no-MI under FES. The X-axis represents time (ms), while the Y-axis indicates the frequency (1-29Hz). The color scale implies the relative PDS from the FES starting point.

4.8.2. Task Performance

Table 4.6 shows the accuracy of each period and classification method. The period consists of the SMR, ACT, and FES period, while the classification method includes LDA, SVM, and the ensemble method. The accuracy was calculated by averaging the 10-fold cross-validation results as defined before.

Table 4.6. Accuracy of each period and classification methods (%)

	SMR period			ACT period			FES period		
	LDA	SVM	Ensemble	LDA	SVM	Ensemble	LDA	SVM	Ensemble
S01	56.29	56.31	59.17	64.04	65.45	69.51	46.29	50.52	48.03
S02	74.31	73.97	76.03	70.23	67.99	73.94	53.71	63.18	58.71
S03	74.28	74.68	76.44	69.30	68.07	70.26	60.00	66.67	62.50
S04	84.06	81.92	83.62	66.40	67.50	70.15	55.05	54.38	53.55
S05	67.90	64.92	67.50	58.75	63.07	64.24	54.85	60.23	55.83
S06	67.23	65.51	68.04	70.27	73.64	76.59	53.33	62.73	61.74
S07	75.48	78.23	79.11	66.52	70.27	73.91	58.64	59.85	60.91
S08	75.00	74.50	78.00	70.20	70.02	71.43	73.00	72.18	74.00
Mean	71.82	71.26	73.49	66.96	68.25	71.25	56.86	61.22	59.41
STD	7.61	7.81	7.42	3.78	2.99	3.49	7.20	6.33	7.13

The results of ANOVA are presented in Table 4.7 including two main effects. The table also includes partial η^2 to measure the effect sizes, the proportions of the variability associated with an effect compared to the total variance, characterized by small, medium, and large effect with values of .01, .06, and .14, respectively (Cohen, 1988; Fritz et al., 2012; Richardson, 2011).

Table 4.7. Results of ANOVA for the accuracy

Source	DF	F-Value	Pr > F	Partial η2
Model	15	11.3356	<.0001***	
Period type	2	47.8111	<.0001***	0.63066
Classifier type	2	2.1305	0.1283	0.07071
Period * Classifier	4	0.8506	0.4993	0.05728
Subject	7	9.5356	<.0001***	0.54378

** p < 0.05, ** p < 0.01, ***p < 0.001*

The results showed that the average accuracies between three periods were significantly different ($F_{2, 56} = 47.8111$; $p < .00001^{***}$; $\eta_p^2 = 0.63066$), but the main effect of classifier types and interaction were not significant. Tukey's HSD was tested to determine significant differences in the main effects of MI period as shown in Figure 4.18. The results showed that the average accuracy of the SMR period was significantly higher than that of the ACT period, and that of ACT period was significantly higher than that of the FES period. Furthermore, the results of t-test showed that the average accuracy of the ACT period (68.82%; $t_{23} = 4.10$, $p < 0.001^{***}$) was significantly higher than the true chance level (57.43%), but the FES period (59.16%; $t_{23} = 1.17$, $p = 0.2558$) was not significant.

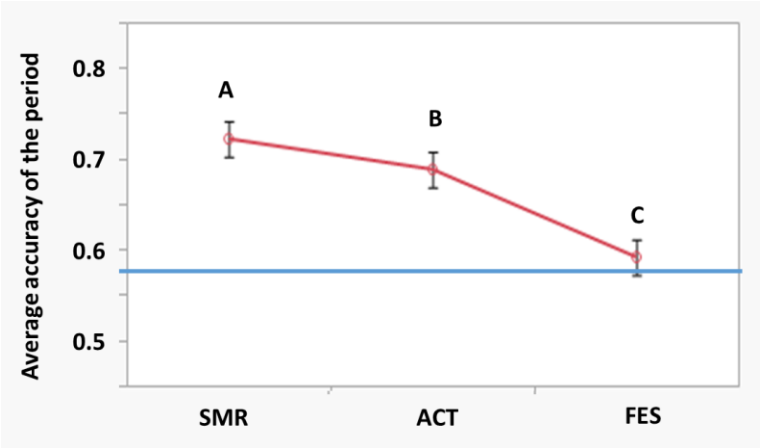


Figure 4.18. Least squares means of the accuracy for each period

Different letters above bars show a significant difference ($p < 0.05$), and the blue vertical line indicates the true chance level.

Tukey's HSD was also tested to determine significant differences in the main effects of classifier type as shown in Figure 4.19. Although the average accuracy of the ensemble method was higher than others, the results of the statistical analysis showed that the average accuracies between classifiers were not significantly different.

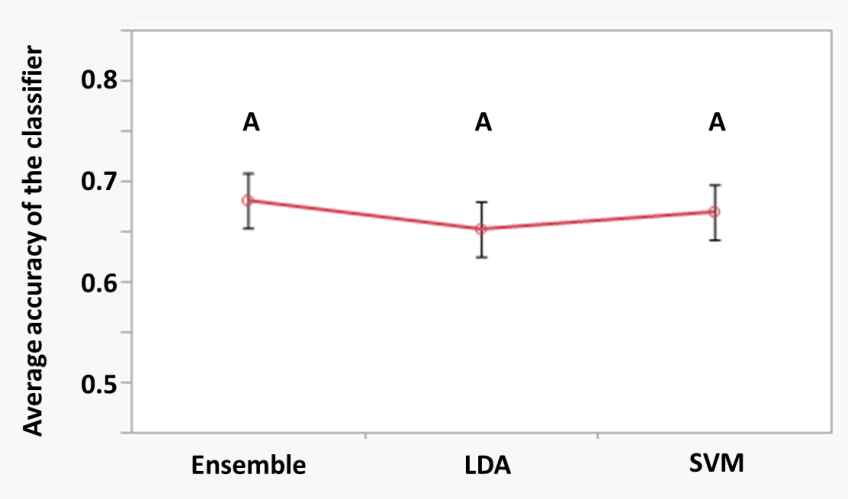


Figure 4.19. Least squares means of the accuracy for each classifier

Different letters above bars show a significant difference ($p < 0.05$).

4.9. Discussion

Study 2 investigated the feasibility of classifying not only a 2-class MI task in a single hand but also detecting the presence of MI-evoked SMRs when FES was activated.

The results of brain activity during the SMR period showed that the brain signals before and after staring MI tasks had different patterns. These distinctive patterns are very important features that allow the classifier to distinguish the presence of MIs. In addition, the results of brain activity during the ACT period showed that the application of two different MI tasks, such as SOG and FCO, could evoke the distinct SMR features. The ERSP results illustrate that the SMR patterns induced by FCO-MI were more dynamic than that induced by SOG-MI. Furthermore, the number of ERD/ERS patterns was different between two MI tasks, where SOG evoked a set of ERD/ERS while FCO elicited repetitive ERD/ERS patterns. The ability of 2-class MI tasks to derive distinct features can play an important role in increasing classification accuracy. As expected, the results of statistical analysis showed that the classification accuracy of a 2-class MI task was significantly higher than the true chance level. Therefore, the null hypothesis of H2.1 was rejected in favor of the alternative hypothesis, which states that the classification accuracy to classify a 2-class MI task in a single hand is significantly higher than the true chance level. This result could be extended to any SMR-based BCI system, as well as other SMR-based FES-BCI systems.

However, the results of brain activity during the FES period showed that there were vague patterns to visually distinguish each condition, including with and without MI tasks, when FES was activated. Furthermore, the results of ICA showed that some of the independent components were contaminated by FES, including electrical noise and FES-driven hand

movements. The results of statistical analysis also showed that the accuracy of the FES period was not significantly higher than the true chance level. Therefore, the null hypothesis of H2.2 was not rejected. The reasons for these results are as follows: First, the duration of the FES period might be too short to stabilize the excited brain signal due to electrical stimulation. Second, electrical artifacts from the FES might be not completely grounded by the anti-static wrist strap applied to the opposite hand of the affected forearm with the FES electrode. Third, according to the post-experiment questionnaire, a few participants mentioned that while the FES system was in operation, it was difficult to stay calm without movement-related imagination. Some possible solutions to solve this issue are to use different types of brain features, such as visual stimuli, or other physical actions, such as closing the eyes.

The results of the classification type showed that the average accuracy of the ensemble method was higher than other methods, but statistical analysis showed that the difference between classification types was not significant. One possible reason is that the accuracy of classification among subjects showed a large variation due to the difference in individual ability. To address this issue, the accuracy of classification was standardized within participants, and ANOVA analysis was conducted again. The results of ANOVA showed that the standardized accuracy between classification types was significantly different ($F_{2, 56}$ = 3.347; p = 0.0424*; η_p^2 = 0.10677) as shown in Table 4.8 and Figure 4.20. Therefore, the modified null hypothesis of H2.3a was rejected in favor of the alternative hypothesis, which states that the standardized classification accuracy of the ensemble method is significantly higher than that of LDA.

Table 4.8. Results of ANOVA for the standardized accuracy

Source	DF	F-Value	Pr > F	Partial η2
Model	15	7.6485	<.0001***	
Period	2	51.7093	<.0001***	0.64872
Classifier	2	3.347	0.0424*	0.10677
Period * Classifier	4	1.1536	0.3411	0.07613
Subject	7	0	1	0

** p < 0.05, ** p < 0.01, ***p < 0.001*

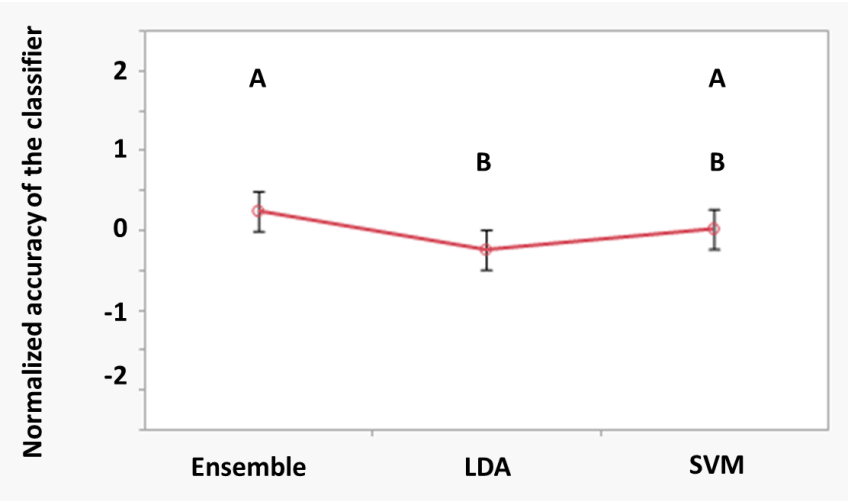


Figure 4.20. Least squares means of the standardized accuracy for each period
Different letters above bars show a significant difference (p < 0.05).

From the post-experiment questionnaire, one participant mentioned that "The duration of the session was a bit too long and left me tired. I am easily tired after the stroke". There were a few other participants who verbally mentioned that it was difficult to maintain mental imagination while minimizing physical movements throughout the experiment (around 40 minutes).

Finally, two classification features including the user-specific classifier parameter set and a probability weight for the ensemble method were constructed. The proposed SMR-based BCI system for FES control including two classification features was then utilized for online BCI experiments in Study 3.

5. STUDY 3: VALIDATION OF THE PROPOSED BCI-FES SYSTEM

5.1. Objectives

The purpose of Study 3 was to assess the feasibility of the proposed BCI-FES system to conduct goal-oriented tasks under the semi-asynchronous mode by: (1) classifying a 2-class MI task in a single hand, and (2) decoding active and passive SMRs. In addition, the effects of the existence of electrical stimulation during MI tasks (No-FES vs. Yes-FES) and the application of the adaptive learning method (before-learning vs. after-learning) on task performance were also assessed.

In order to achieve the purpose, participants were asked to conduct an online BCI experiment to perform a predetermined set of actions representing common ADLs, such as moving an object. The sequence of the tasks is as follows; (1) open a hand as a preceding action to catch an object, such as a small ball; (2) return to comfortable hand position from extension by stopping FES; (3) grab the ball with enough strength; (4) hold the ball, and (5) drop the ball. Participants were asked to perform this sequential task by using the proposed SMR-based BCI-controlled FES system. The user specific parameters identified in the previous experiments were set as parameters of FES and BCI classifiers.

After the online BCI experiment, the brain signals were also analyzed to find features that distinguished between successful and failed trials, to characterize features from those who performed well, and to investigate the characteristics of EEG signals measured in synchronous and asynchronous experiments.

5.2. Methods

5.2.1. Participants

The same patients who participated in Study 2 continued this experiment either after a 20-minute break or when the participants felt ready. Any patients who were displeased with the experiment could cease at any time, but no one had chosen to withdraw.

5.2.2. Apparatus

To mimic ADLs, participants were asked to hold, move, and release a small ball from an initial position to a target position by utilizing the proposed SMR-based BCI-controlled FES system. The initial and target positions of the ball were set within the comfortable distance in front of participants. The distance between the initial and the target position was set to 10 cm. The entire experiment procedure was video-recorded for further analysis.

5.2.3. Experiment Mode

There are two different modes of experiment that are mainly applied in BCI studies (Pfurtscheller & Neuper, 2001). The first mode is a synchronous, cue-based experiment which is the same type of experiment performed in Study 2. In this type of experiment, the participants are usually provided with visual, auditory, or tactile cues and perform tasks accordingly in a fixed time interval. Afterward, through the offline analysis, the measured brain signals are divided into groups according to the cues, and the brain features representing each group are

extracted. Classifier parameters are then generated to best distinguish each group based on the features.

The second mode is an asynchronous, self-paced experiment where the users perform a task at their own pace rather than following the cues. The advantage of the asynchronous experiment is that the BCI system can be more realistic and flexible, because it allows the user to perform the desired operation at their own pace (Tonet et al., 2006). It would be very useful for patients to be able to control the impaired body solely through MIs. However, since it is difficult to know when the user performed MI tasks, the asynchronous mode has a critical issue such that the classification accuracy is low due to the high false positive ratio (Ortner, Allison, Korisek, Gaggl, & Pfurtscheller, 2011). Due to the low accuracy of the MI tasks because of the high false positive ratio, it is somewhat difficult to perform experiments on patients in a completely asynchronous situation. As a result, asynchronous BCI research has not been studied as much compared to synchronous BCI research (Lotte et al., 2007).

More training in synchronous experiments could help to solve this issue, but long-lasting BCI training is not easy for participants with impaired physical conditions (and/or mental conditions such as attention deficits after stroke and TBI) since it requires participants to sit down and focus on repetitive mental tasks while minimizing movement. Furthermore, the results of synchronous experiments are not always guaranteed to be the same results as those of asynchronous experiments. This is due to cue differences (Yes vs. No), analysis time differences (fixed vs. variable), and the nature of brain signals which have non-stationarity and inter- and intra-variability (Nicolas-Alonso & Gomez-Gil, 2012).

Alternatively, we can consider increasing the accuracy through more practice in the same environment as the asynchronous mode, but there are also the following issues. First, it is difficult to know when the patient has successfully performed MIs, as knowing this information is essential to categorize the EEG signals into two group (Yes-SMR vs. No-SMR) to initiate the FES system. Second, if the errors, either false positive or false negative, are accumulated, the participants will be easily confused and frustrated. Finally, an additional time required to correct the erroneous movements will increase the duration of the experiment, and we should take into consideration that prolonged FES may increase muscle fatigue in patients.

Thus, in this experiment, a semi-asynchronous mode for performing a fixed sequence was proposed. This mode has three important features that combine the advantages of both synchronous and asynchronous modes as follows: (1) a fixed sequence of tasks to clarify what the user needed to do; (2) error-free results to prevent participants from being confused or exhausted, and (3) initiating the FES system by detecting SMRs similar to the asynchronous mode. Under the proposed semi-asynchronous mode, participants would be free from confusion and frustration while using the SMR-based BCI-controlled FES system at their own pace. Furthermore, the experimenter can enhance the classification performance by adjusting the classifier parameters using the most recently measured brain signals under this mode, also known as adaptive machine learning (Pfurtscheller & Neuper, 2001; Vidaurre, Sannelli, Müller, & Blankertz, 2011; Wolpaw & McFarland, 2004).

5.2.4. Procedure

Participants were asked to conduct the fixed sequence MI tasks according to a specific goal. Figure 5.1 shows the sequence of tasks that participants were asked to perform. The BCI tasks consisted of (1) opening the hand with FCO MIs similar to the previous study; (2) stopping FES system by not imagining any action similar to "stop imagination"; (3) grasping a ball with SOG MIs; (4) moving the ball to the target position without going through the BCI system, and (5) holding the ball on the target position by continuously imagining SOG. In this experiment, patients were asked to perform all tasks as quickly as possible, except the 'holding the ball' task which should last as long as possible, using the appropriate MIs trained in the previous experiment.

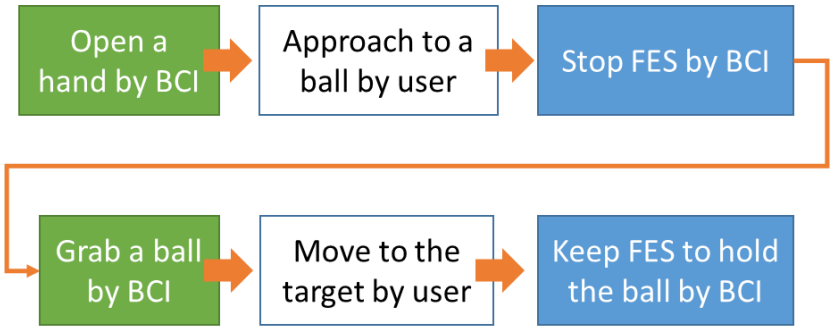


Figure 5.1. Sequence of the predefined tasks in Study 3

In Figure 5.1, the colored boxes represent the tasks that the participant should perform through the BCI system, and the white boxes represent the tasks that the participant was asked to perform without using the BCI system. The green boxes on the left indicate MI tasks without FES, and the blue boxes in the middle show the tasks performed under FES. The following describes each step that participants were asked to perform in detail.

Step 1 – Open a hand

First, participants were asked to perform the opening MI task by imagining FCO trained in the previous experiment. Once the BCI system detected an FCO-related SMR, the FES system was activated for an opening motion of 5 seconds. If the system did not detect the FCO-related SMR in the maximum analysis time (6 seconds), then the system was automatically started so that the experiment time did not increase excessively. Afterward, the participants were asked to move their hand near a ball to be ready to grab.

Step 2 – Stop FES

After five seconds, the participants were asked to stop the FES system as soon as possible without imagining any motion similar to "stop imagination" in Study 2. When the BCI system detected the absence of MI, the FES system stopped working. To prevent excessive muscle fatigue and discomfort, if participants could not stop the FES system in the maximum analysis time, the system automatically stopped operating. Participants were then given a 10-second break to stabilize excited brain activity from the physical movements and electrical stimulation, and the BCI system also stopped classifying brain signals during the break.

Step 3- Grab a ball

After the break, the participants were asked to conduct the SOG MIs to grab the ball. If an SOG-related SMR was detected, the FES system was activated for grasping motion for 5 seconds, and they were asked to move the ball to the target position within 5 seconds. Similar

to Step 1, if the system did not detect the SOG-related SMR in the maximum analysis time, then the system automatically initiated grasping motion.

Step 4 – Hold the ball

After the participants had moved the ball over to the target position, they tried to keep holding the ball for another 5 seconds. To hold the ball, the grasping SMR should be maintained when FES was activated for grasping. If the grasping SMR was successfully maintained during the maximum analysis time, the FES system automatically stopped for safety. This was the task sequence of this experiment necessary to complete one trial.

Participants were asked to conduct two sets of the sequential tasks in each trial, which lasted until all tasks were finished. Figure 5.2 illustrates the rules, MI tasks, and sequence of the tasks. A total of 20 trials were conducted during the experiment as shown in Figure 5.3. The completion time varied due to the different performance levels between participants, but the average completion time was around 40 minutes.

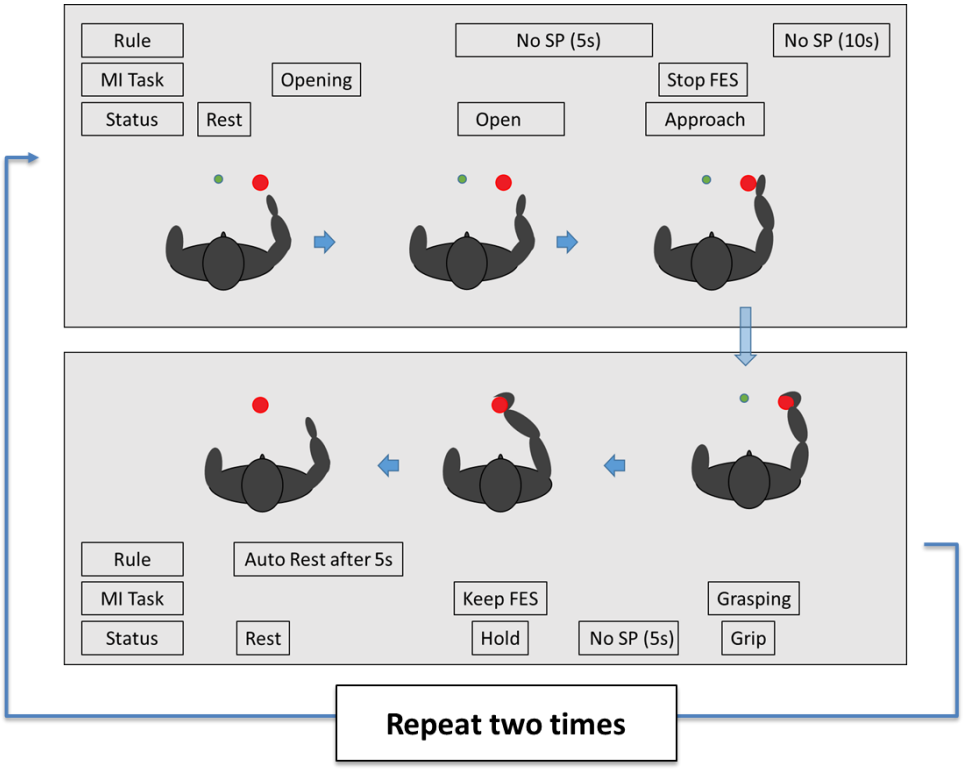


Figure 5.2. Sequence of the tasks with rule (in seconds), MI tasks, and status

A red circle presents the ball and a green circle indicates a target position. SP indicates signal processing.

Session 1	1st trial				Rest (10s)	2nd trial			
	No-FES	Yes-FES	No-FES	Yes-FES		No	Yes	No	Yes
MI Task	Open	Stop	Grasp	Keep		E	G	H	R
	1	1	1	1		1	1	1	1
Break (1 min) ...									
Session 5	9th trial				Rest (10s)	10th trial			
	No-FES	Yes-FES	No-FES	Yes-FES		No	Yes	No	Yes
SMR Task	Open	Stop	Grasp	Keep		E	G	H	R
	1	1	1	1		1	1	1	1
Break (1 min), and applying adaptive learning									
Sesison 6	11th trials				Rest (10s)	12th trial			
	No-FES	Yes-FES	No-FES	Yes-FES		No	Yes	No	Yes
MI Task	Open	Stop	Grasp	Keep		E	G	H	R
	1	1	1	1		1	1	1	1
Break (1 min) ...									
Session 10	19th trial				Rest (10s)	20th trial			
	No-FES	Yes-FES	No-FES	Yes-FES		No	Yes	No	Yes
SMR Task	Open	Stop	Grasp	Keep		E	G	H	R
	1	1	1	1		1	1	1	1

Figure 5.3. Experimental design of Study 3

5.3. Signal Processing

5.3.1. Signal Acquisition and Preprocessing

The signal acquisition and preprocessing procedures were identical to Study 2 except the artifact removal and ICA procedure, because these procedures require additional computational times and visual inspections that are not suitable for real-time experiments (Jung et al., 2000).

5.3.2. Feature Extraction and Selection

In this study, the CSP and ERD/ERS features used user-specific CSP projection matrix and ERD / ERS weighted matrix obtained as the results of the offline analysis of Study 2.

5.3.3. Classification

For the online classification, the ensemble method was utilized as the results of the previous study showed that performance of the ensemble method was significantly higher than the LDA method. During the 20-minute break after Study 2, user-specific classifier parameters including weight vectors for each classifier were determined via the offline analysis.

During the online experiment, EEG signals were categorized as three periods similar to Study 2 including the SMR period (to detect the SMR features to initiate the FES system), the ACT period (classifying different MIs including grasping and opening), and the FES period (to either keep or stop the FES system). One difference was that the incoming signal was the same, but the role was changed according to the current goal. For example, if the current status

is to try to perform an opening a hand, then the current period is defined as the SMR period. If the SMR feature is detected, then the role of the same EEG dataset is changed to the ACT period. Therefore, detecting SMRs and classifying a 2-class MI task are performed sequentially. However, if SMR-related brain features are not detected, the current role is not changed and the SMR period is maintained. On the contrary, if a target role either grasping or opening is not detected during the ACT period, then the current status is set back to the SMR period. When the BCI system detects only the target role from the ACT period, the FES system is activated according to the decision from the BCI system.

5.3.4. Adaptive Learning

When participants completed the first 10 trials, the adaptive learning method was applied to adjust classifier parameters. Many different adaptive learning methods are available, and the advantages and computational time of each method vary. More elaborate adaptive learning methods might yield higher accuracy, but they require more computational time (Vidaurre et al., 2011). Adaptive learning methods can be divided into two groups, supervised and unsupervised learning (Vidaurre, Kawanabe, Von Bünau, Blankertz, & Müller, 2011). As the names imply, supervised learning requires the class information, while unsupervised learning does not. As Vidaurre et al. (2011) recommended due to ease and good performance, Pooled mean (PMean) adaptive estimation method was chosen, and the equation of PMean estimation is shown in Equation 5.1. Since this method is the unsupervised adaptive learning method, it can also be utilized in the asynchronous mode.

Equation 5.1. Pooled mean (PMean) adaptive estimation

$$\mu_t = (1-\eta)\mu_{t-1} + \eta x_t \qquad w0_t = -w^T(\mu_t)$$

where

$W0_t$ = the bias of the classifier at trial t

η = the updating coefficient (0.1)

x_t = the new feature obtained at trial t

5.4. Independent Variables

In this experiment, two IVs were manipulated: an FES existence type (No-FES vs. Yes-FES) and a learning type (before-learning vs. after-learning). The FES existence type indicates the existence of electrical stimulation during MI tasks, and has two levels: No-FES (opening and grasping, steps 1 and 3, respectively) and Yes-FES (stop and keep, steps 2 and 4, respectively). The learning type indicates the application of the adaptive learning method during the experiment, and the learning type also has two levels: Before-learning and After-learning. The two IVs are summarized in Table 5.1

Table 5.1. Summary of IVs in Study 3

IV	Levels	
FES existence type	No-FES (grasping or opening)	Yes-FES (stop or keep)
Learning type	Before-learning	After-learning

5.5. Dependent Variables

DVs were categorized into three types of variables same as the first experiment: Brain activity, task performance, and subjective assessment. Task performance and subjective assessment were then statistically analyzed with ANOVA tests.

5.5.1. Brain activity

The brain activity analysis was applied to validate and represent the SMR brain features with relative band power during No-FES and Yes-FES periods similar to Study 2.

5.5.2. Task Performance

Completion rate (%)

A completion rate is defined as how quickly grasping, opening, and stop FES operation have been performed, or how long it has lasted during the keep FES task (Kuiken et al., 2009; Wodlinger et al., 2015). For example, the completion rate will be 100% if the predetermined MI tasks to be performed succeeds in only one attempt (0 seconds). However, if the target SMR cannot be performed before the maximum analysis time (6 seconds), the completion rate would be 0%. On the contrary, in the case of performing the keep-SMR task, the SMR must be maintained for 6 seconds, the maximum analysis time, to achieve 100% completion rate. As the completion rate was calculated based on elapsed time, the completion rate was highly related to the completion time. Lower completion rate results in longer completion time.

Therefore, the completion rate was analyzed rather than the completion time which cannot represent the ‘keep FES’ task. The completion rate can be calculated by Equation 5.2.

Equation 5.2. Completion rate (%)

$$\text{Completion Rate} = \frac{\text{Maximum Analysis Time} - \text{Elpased Time}}{\text{Maximum Analysis Time}} \quad \text{except keep FES task} \qquad \text{... (a)}$$

$$= \frac{\text{Elpased Time}}{\text{Maximum Analysis Time}} \quad \text{for keep FES task} \qquad \text{... (b)}$$

Accuracy (%)

The successful task implies that the MI tasks were performed without error. However, in the case of semi-asynchronous and asynchronous experiments rather than time-locked and cue-based experiments, the definition of error is not clear. This is because if the operation does not occur because the SMR-related features are not detected during the SMR period, it is a delay rather than an error requiring additional work to be corrected. Also, due to the nature of the asynchronous experiment, it is difficult to distinguish whether the delay is intended due to a failure to implement MIs. However, from another point of view, it is difficult to define this as a successful task performance if the delay caused by MI induction failure is long enough to affect BCI performance. Therefore, the accuracy in this experiment was defined as follows; (1) if an incorrect decision was made during SMR period (i.e. no SMR was detecting), then it belongs to a delay until the maximum analysis time (6 seconds); (2) if an incorrect decision was made during ACT (i.e. the target action was ‘opening’, but classified as ‘grasping’, and vice versa), then it belongs to an error, and (3) if an incorrect decision was made during FES period (i.e. the action should be ‘keep’, but classified as ‘stop’, and vice versa), then it belongs

to an error. The structure of the classification algorithms utilized in this study also agree on this argument, because even if it fails to detect the SMR function, it is not necessary to correct this error, but only a delay of 1 second occurs.

Sensitivity

Confusion matrix analysis, also known as contingency tables, was conducted to analyze correct positive and false positive rates (McNicol, 2005). The number of misclassifications was analyzed through the offline analysis after the semi-asynchronous experiment was finished. In this experiment, the definition of correct and error are set based on the definition of accuracy.

Information Transfer Rate

Many BCI studies have utilized Information Transfer Rate (ITR) to evaluate performance of BCI systems which can convey the amount of information per time (bits/minute) in terms of the accuracy and speed (Wolpaw, Ramoser, McFarland, & Pfurtscheller, 1998). When applying ITR, the equal probability of error assumption should be considered to prevent unexpected results (Thompson, Blain-Moraes, & Huggins, 2013). The equation to calculate ITR is shown in Equation 5.3. From the equation, the number of bits transferred per trial (B) can be obtained, then ITR can be calculated by B/T, where T is the duration of the trial. There were a total of six targets in this experiment (SMR detecting for opening, opening-SMR, stop-SMR, SMR detecting for grasping, grasping-SMR, and keep-SMR. In order to determine the duration of each trial to calculate ITR, the short waiting time

given in the middle of the task was included as the time required for the experiment but did not include the 10-second preliminary time given before the start of the experiment.

Equation 5.3. Equation for the number of bits/trial

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \left(\frac{1 - P}{N - 1} \right)$$

$$ITR = \frac{B}{T}$$

where N = the number of targets, P = the accuracy of trial, T = the duration of each trial

5.5.3. Subjective Assessment

NASA-TLX

When participants completed the experiment in Study 3, they were asked to answer the NASA-TLX questionnaire to measure the subjective mental workload same as Study 2 (Hart & Staveland, 1988). The results of studies were then analyzed to compare changes in the subjective mental workload between two experiment in Studies 2 and 3.

Survey

After the experiment, participants were asked to complete a post-experiment questionnaire including overall satisfaction of the study, personal opinions and any suggestion for future research studies. The results of the survey were summarized in the discussion section.

5.6. Experiment Design and Statistical Analysis

The objectives of the statistical analysis were to test the feasibility and task performance of the proposed SMR-based BCI-controlled FES system under a fixed sequence for each task. To validate the proposed system, performance of participants was evaluated according to completion rate, accuracy, sensitivity, and ITR. In Study 3, an ANOVA test was conducted to evaluate the main effect of IVs, such as the FES existence type and learning type, and interaction effects between two IVs on task performance with participant as a blocking variable. Equation 5.4 and Table 5.2 show the ANOVA model and DF of the model, respectively.

Equation 5.4. ANOVA model in Study 3

$$y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \mathrm{B}_k + \varepsilon_{ijk}$$

Where

i = 1, 2 indexes the FES existence type (yes vs. no)

j = 1, 2 indexes the learning type (before vs. after)

y_{ijk} is task performance of j learning type during i existence type

μ is a reference level

α_i's are the main effects of the FES existence type

β_j's are the main effects of the learning type

B_k is the blocking factors of subject k

$(\alpha\beta)_{ij}$'s are the interaction between the FES existence type & learning type

$\epsilon_{ijk} \sim \mathrm{N}(0, \sigma_\epsilon^2)$

$\mathrm{B}_k \sim \mathrm{N}(0, \sigma_B^2)$

Table 5.2. DF in Equation 5.3

Source	DF
FES existence type	1
Learning type	1
Existence x Learning	1
Subject	7
Error	21
Total	31

ANOVA, two parametric assumptions were assessed in JMP® (SAS institute Inc., Cary, NC) similar Before conducting to Studies 1 and 2. The results in Table 5.3 showed that data satisfied the assumptions of both homoscedasticity and normality of residuals. The result showed that all DVs did not violate the ANOVA assumptions, so two-way ANOVAs were conducted.

Table 5.3. Results of homoscedasticity and normality tests for Study 3

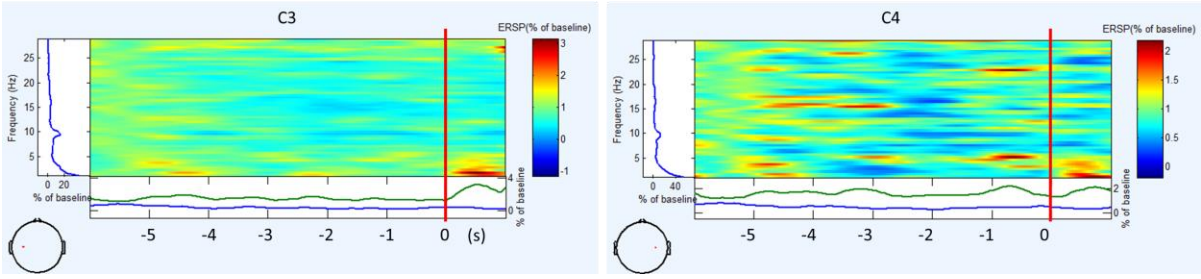
	Shapiro-Wilk Test (Normality)	Brown-Forsythe test (Homoscedasticity)
Completion rate	W = 0.978031 p = 0.7406	$F_{3, 28}$ = 0.1628 p = 0.9205
Accuracy	W = 0.957758 p = 0.2383	$F_{3, 28}$ = 0.0692 p = 0.9759
Sensitivity	W = 0.94603 p = 0.1111	$F_{3, 28}$ = 0.1603 p = 0.9221
ITR	W = 0.969841 p = 0.4950	$F_{3, 28}$ = 1.3495 p = 0.2785

5.7. Results

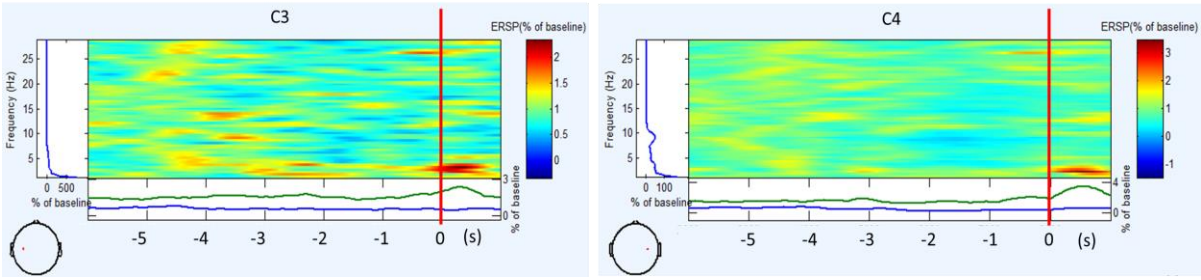
5.7.1. Brain Activity

After the experiment, brain activity of each subject was analyzed to identify the SMR-related brain features in the semi-asynchronous experiments. Unlike the experiments in Study 2, brain signals were only preprocessed with the band-pass filtering method (1-29 Hz), but the automatic artifact rejection and the ICA procedures were not applied for identifying the same brain features used in the online experiment. Figure 5.4 shows that the ERSPs of C3 and C4 from Subjects 'S05' and 'S06' during the No-FES period. Red vertical lines indicate the onset of FES after detecting and classifying SMRs. The X-axis represents the time in seconds before the FES was activated, the Y-axis indicates the frequency (1-29 Hz), and the color map shows the relative PSD.

Since subject 'S05', suffers from left hemiparesis, conducted MI tasks with the left hand, the ERSP of C4 shows more dynamic brain activity compared to that of C3 as shown in Figure 5.4 (a). Similarly, Figure 5.4 shows the ERSP of C3 and C4 from Subject 'S06', who suffers from right hemiparesis, and the results showed that the SMR-related features occurred in the contralateral motor cortex, C3, while the ipsilateral motor cortex did not show dynamic brain activity. In addition, the SMR patterns induced by MI tasks were less distinctive compared to Study 2, because the EEG signals aligned with respect to the onset of FES after detecting and classifying SMRs. Thus, the ERD / ERS patterns were dispersed because the timing of MI tasks was different for each trial.



(a)

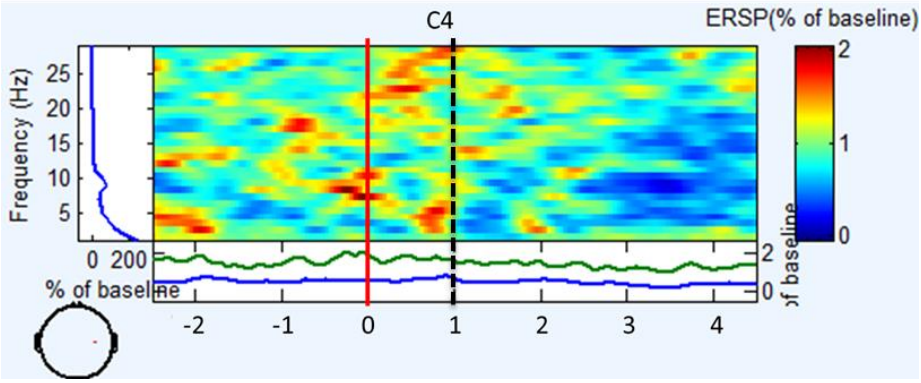


(b)

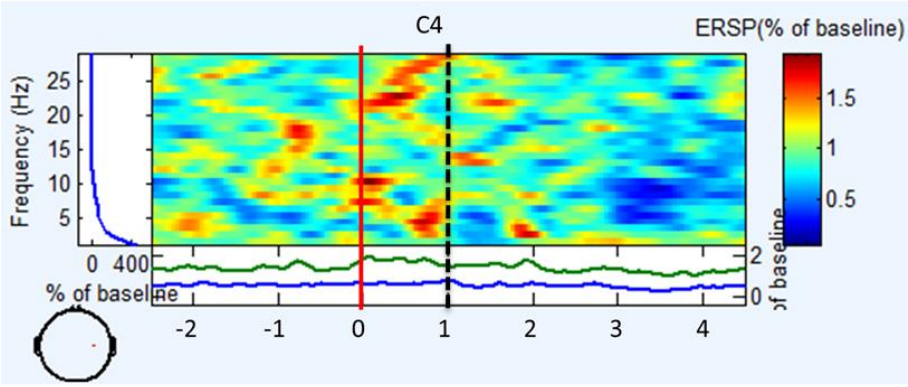
Figure 5.4. ERSPs of C3 and C4 from Subjects 'S05' and 'S06' during the No-FES period

(a) ERSP from Subject 'S05' who suffers from left hemiparesis. (b) ERSP from Subject 'S06', right hemiparesis. Red vertical lines indicate the onset of FES after detecting and classifying SMRs. The X-axis represents the time in seconds before the FES was activated, the Y-axis represents the frequency (1-29 Hz), and the color map shows the relative PSD.

Figure 5.5 shows the ERSPs of C4 from Subject 'S04' (left hemiparesis) during the Yes-FES period including 'keep FES' and 'stop FES' trials. Red vertical lines indicate the onset of FES, and block vertical dotted lines represent the end of ramp time. The X-axis indicates the time in seconds before and after the onset of FES (at the red vertical lines), the Y-axis represents the frequency (1-29 Hz), and the color map shows the relative PSD. Figure 5.5 (a) displays the ERSPs of C4 with the 'keep FES' trials, while Figure 5.5 (b) illustrates that with the 'stop FES' trials. As seen in the figures, the brain patterns between two conditions are not distinctive due to FES artifacts and FES-driven passive-movement-evoked SMRs although little more active patterns were found during the 'keep FES' trials.



(a)



(b)

Figure 5.5. ERSPs of C4 from Subject 'S04' during the Yes-FES period

(a) ERSP during the 'keep FES' trials. (b) ERSP during 'stop FES' trials. Red vertical lines indicate the onset of FES, and block vertical dotted lines represent the end of ramp time. The X-axis indicates the time in seconds before and after the onset of FES (at the red vertical lines), the Y-axis represents the frequency (1-29 Hz), and the color map shows the relative PSD.

5.7.2. Task Performance

Table 5.4 summarizes the completion rate of each task. As the goal of 'keep FES' was to maintain grasping FES as long as possible by continuing SOG MI tasks, the completion rate of 'keep FES' was calculated by Equation 5.2 (b). The results showed that the average completion rate of each task including 'grasping,' 'opening,' 'keep FES,' and 'stop FES' were

55.94%, 53.44%, 62.08% and 57.71%, respectively. There were some excessive values between subjects, such as the completion rate of ‘opening’ action for subjects subject ‘S04’ and subject ‘S03’ are 93.3% and 29.2%, respectively. Furthermore, within the participant, there were large variations in the completion rate. For example, Subject 'S04' showed the highest completion rate (95%) for the ‘stop FES’ task among all the participants, but that for ‘keep FES’ was the lowest completion rate (13.3%).

Table 5.4. Average completion rate for each task (%)

	Grasping	Opening	No-FES Average	Keep	Stop	Yes-FES Average	Grand Average
S01	71.7	70.8	71.3	31.7	68.3	50.0	60.6
S02	71.7	60.8	66.3	26.7	70.0	48.3	57.3
S03	38.3	29.2	33.8	40.0	84.2	62.1	47.9
S04	42.5	93.3	67.9	13.3	95.0	54.2	61.0
S05	78.3	50.0	64.2	90.0	71.7	80.8	72.5
S06	73.3	72.5	72.9	52.5	59.2	55.8	64.4
S07	45.0	55.0	50.0	68.3	22.5	45.4	47.7
S08	65.0	90.0	77.5	51.7	40.0	45.8	61.7
STD	15.0	19.8	13.4	22.9	21.8	11.0	19.9
Average	55.7	65.2	63.0	46.8	63.9	55.3	

The average completion rate for the ‘keep FES’ task was lower than other values, and the reason is that the ‘keep FES’ task required six successive successes to obtain 100% completion rate, while other tasks only needed the first-time success.

Table 5.5 shows the average completion rate for each IV. The results showed that the average completion rate of the No-FES period was higher than that of the Yes-FES period similar to experiment 2. Furthermore, the average completion rate after applying the adaptive learning method was higher than before.

Table 5.5. Average completion rate of each IV (%)

	Before-Learning			After-Learning			
	No-FES	Yes-FES	Average	No-FES	Yes-FES	Average	Grand
S01	71.7	49.2	60.4	70.8	50.0	60.4	60.4
S02	57.5	39.2	48.3	75.0	48.3	61.7	55.0
S03	44.2	62.5	53.3	23.3	62.1	42.7	48.0
S04	55.8	49.2	52.5	80.0	54.2	67.1	59.8
S05	58.3	72.5	65.4	70.0	80.8	75.4	70.4
S06	73.3	50.0	61.7	72.5	55.8	64.2	62.9
S07	40.0	43.3	41.7	60.0	45.4	52.7	47.2
S08	46.7	61.7	54.2	45.0	65.0	55.0	54.6
STD	11.38	10.41	7.19	17.80	10.73	9.26	7.25
Average	55.94	53.44	54.69	62.08	57.71	59.90	

The accuracy of each task is shown in Table 5.6. The results showed that the accuracy of the No-FES period was little higher than that of the Yes-FES period, but the differences were not large. There was some evidence that the classifiers might be biased to a certain direction because Subject ‘S05’ tended to say ‘keep FES,’ while Subject ‘04’ tended to say ‘stop FES.’

Table 5.6. Accuracy of each task (%)

	Grasping	Opening	No-FES Average	Keep	Stop	Yes-FES Average	Grand Average
S01	60.0	55.0	57.5	50.0	45.0	47.5	52.5
S02	65.0	55.0	60.0	35.0	55.0	45.0	52.5
S03	30.0	35.0	32.5	50.0	60.0	55.0	43.8
S04	40.0	85.0	62.5	15.0	80.0	47.5	55.0
S05	70.0	45.0	57.5	90.0	45.0	67.5	62.5
S06	70.0	60.0	65.0	60.0	55.0	57.5	61.3
S07	35.0	50.0	42.5	75.0	10.0	42.5	42.5
S08	65.0	70.0	67.5	65.0	10.0	37.5	52.5
STD	15.5	14.3	11.2	21.8	22.6	8.9	6.7
Average	54.4	56.9	55.6	55.0	45.0	50.0	

Table 5.7 shows the accuracy of each IV, and the results showed that the accuracy of each FES condition increased after applying learning. It indicates that the adaptive learning procedure enhanced the identifiability of both classification algorithms. Between two periods, the improvement of the No-FES period was higher than that of the Yes-FES period.

Table 5.7. Accuracy of each IV (%)

	Before-Learning			After-Learning			
	No-FES	Yes-FES	Average	No-FES	Yes-FES	Average	Grand
S01	55.0	45.0	50.0	60.0	50.0	55.0	55.0
S02	50.0	30.0	40.0	70.0	60.0	65.0	65.0
S03	30.0	55.0	42.5	35.0	55.0	45.0	45.0
S04	55.0	40.0	47.5	70.0	55.0	62.5	62.5
S05	50.0	55.0	52.5	65.0	80.0	72.5	72.5
S06	60.0	55.0	57.5	70.0	60.0	65.0	65.0
S07	30.0	40.0	35.0	55.0	45.0	50.0	50.0
S08	65.0	40.0	52.5	70.0	35.0	52.5	52.5
STD	12.1	8.7	7.0	11.4	12.2	8.7	8.7
Average	49.4	45.0	47.2	61.9	55.0	58.4	58.4

Table 5.8 shows the sensitivity, specificity, and PPV of each task. The higher sensitivity indicates the ability to say ‘Yes’ when the answer was actually ‘Yes,’ while higher specificity implies the ability to say ‘No’ when the answer was ‘No’ (Criqui, Fronek, Klauber, Barrett-Connor, & Gabriel, 1985). In the table, Positive and Predictive Value (PPV) indicates the ratio of true positives to the summation of true and false positives. With this analysis, the sensitivity of each subject was analyzed as a performance criterion. As shown in the tables, many results were biased towards one class. For example, the results of Subject ‘S04’ indicated the participant more likely said ‘Yes,’ than ‘No,’ and this tendency could cause higher false positive rate. Furthermore, the decisions during the Yes-FES period were more biased than that of the No-FES period, and it would cause more errors. In this case, although the accuracy of one class is high, it cannot guarantee the overall accuracy is also high.

Table 5.8. Sensitivity, specificity, and PPV of two IVs (%)
‘Sens’ indicates the sensitivity, and ‘Spec’ implies the specificity

	Before-Learning						After-Learning					
	No-FES			Yes-FES			No-FES			Yes-FES		
	Sens	Spec	PPV	Sens	Spec	PPV	Sens	Spec	PPV	Sens	Spec	PPV
S01	50	60	56	50	40	45	60	60	60	40	60	50
S02	30	70	50	40	20	33	80	60	67	70	50	58
S03	40	20	33	60	50	55	30	40	33	60	50	55
S04	90	20	53	80	0	44	80	60	67	80	30	53
S05	30	70	50	30	80	60	60	70	67	60	100	100
S06	60	60	60	30	80	60	60	80	75	80	40	57
S07	40	20	33	10	70	25	60	50	55	10	80	33
S08	70	60	64	10	70	25	70	70	70	10	60	20
Avg	51	48	50	39	51	43	63	61	62	51	59	53

Figure 5.6 shows four ROC curves for each IV combination. As shown in the figure, performance of a classifier under the Yes-FES condition before applying adaptive learning was less than 50% (shaped as under curve), while the No-FES period after applying adaptive learning showed the greater classification ability. Furthermore, after applying the adaptive learning method, the accuracies of both FES existence types increased.

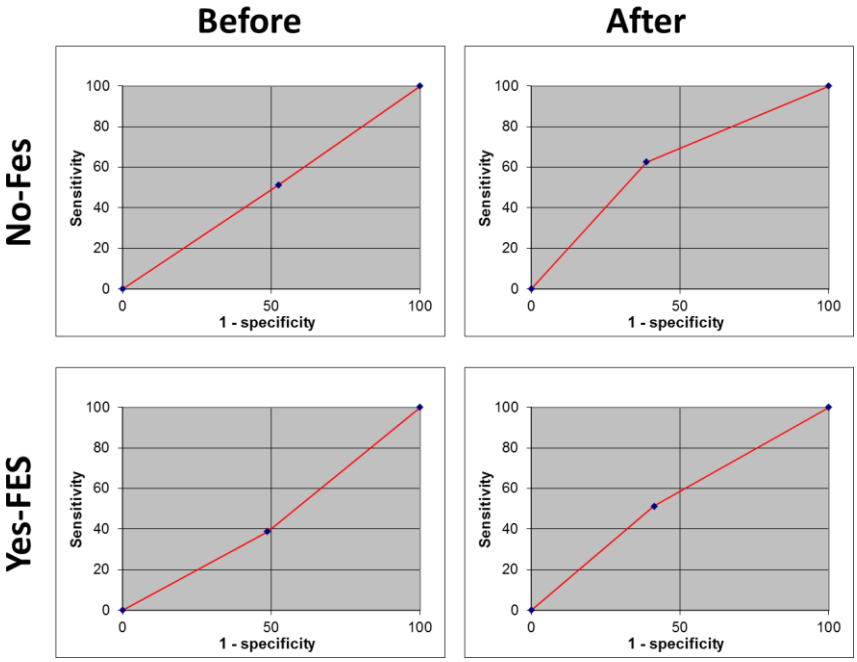


Figure 5.6. ROC curves for two IVs

Table 5.9 shows the ITR of each IV, and ITR values increased a little bit after applying the adaptive learning method, but the difference was great. The results of ITR also indicated that performance of the proposed SMR-based BCI system fell into the average ITR ranges (10 – 25 bit/min) (Wolpaw et al., 2002).

Table 5.9. ITR for each IV (bit/min)

	Before-Learning			After-Learning			Grand
	No-FES	Yes-FES	Average	No-FES	Yes-FES	Average	
S01	13.12	12.71	12.91	12.87	13.03	12.95	12.93
S02	11.81	14.13	12.97	12.24	13.47	12.86	12.91
S03	10.80	12.39	11.60	14.03	9.53	11.78	11.69
S04	11.68	15.91	13.79	14.96	14.03	14.50	14.14
S05	11.88	10.69	11.29	10.47	12.95	11.71	11.50
S06	13.29	10.10	11.70	13.29	13.20	13.25	12.47
S07	10.52	10.10	10.31	9.40	12.03	10.71	10.51
S08	13.47	10.52	12.00	11.10	14.03	12.56	12.28
Avg	12.07	12.07	12.07	12.29	12.78	12.54	12.30

An ANOVA was also performed to test the main effects of IVs, the existence of FES and the learning type, and interactions between IVs with participant as a blocking variable on the completion rate and ITR, separately. As shown in Table 5.10, there were no significant main and interaction effects for both model.

Table 5.10. ANOVA results for the completion rate

Source	DF	F-Value	Pr > F	Partial η2
Model	10	1.5284	0.1979	
FES Existence Type	1	2.5584	0.1246	0.1086
Learning Type	1	2.2875	0.1453	0.09823
FES * Learning	1	0.003	0.9571	0.00014
Subject	7	1.4907	0.2243	0.33195

** $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$*

Table 5.11. ANOVA results for ITR

Source	DF	F-Value	Pr > F	Partial η2
Model	10	1.6524	0.1595	
FES Existence Type	1	0.2146	0.6479	0.01012
Learning Type	1	0.7999	0.3813	0.03669
FES * Learning	1	0.2191	0.6446	0.01032
Subject	7	2.1844	0.0785	0.42134

** p < 0.05, ** p < 0.01, ***p < 0.001*

An ANOVA was also performed to test the main effects of IVs, the existence of FES and the learning type, and interactions between IVs with participant as a blocking variable on accuracy. Table 5.12 shows that there were significant differences in learning type ($F_{1, 21}$ = 8.2273; p = 0.0092**; η_p^2 = 0.28149), but the main effect of the FES existence type and interaction effect were not significant. In addition, Tukey's HSD was tested for post-hoc analysis as shown in Table 5.13, and the results showed that the average accuracy during the No-FES period after applying adaptive learning was significantly higher than that during the Yes-FES period before applying adaptive learning.

Table 5.12. ANOVA results for accuracy

Source	DF	F-Value	Pr > F	Partial η2
Model	10	2.2041	0.0611	
FES Existence Type	1	2.0568	0.1662	0.08921
Learning Type	1	8.2273	0.0092**	0.28149
FES * Learning	1	0.1016	0.7531	0.00481
Subject	7	1.6651	0.1722	0.35692

** p < 0.05, ** p < 0.01, ***p < 0.001*

Table 5.13. Results of Tukey' HSD test

Level			Least Square Mean
No-FES, Adaptive	A		0.61875
Yes-FES, Adaptive	A	B	0.55000
No-FES, No adaptive	A	B	0.49375
Yes-FES, No adaptive		B	0.45000

An ANOVA was also performed to test the main effects of IVs and interactions between IVs in the sensitivity. As shown in Table 5.14, the average sensitivities between IVs were significant different, but there were no significant differences in any effects except the blocking factors. The results of the post-hoc analysis also did not show any significant difference for all IVs.

Table 5.14. ANOVA results for the averaged sensitivity

Source	DF	F-Value	Pr > F	Partial η2
Model	10	2.3480	0.0478*	
FES Existence Type	1	2.9741	0.0993	0.12405
Learning Type	1	2.9741	0.0993	0.12405
FES * Learning	1	0.0082	0.9285	0.00039
Subject	7	2.5033	0.0489*	0.45488

** p < 0.05, ** p < 0.01, ***p < 0.001*

5.7.3. Subjective Assessment

NASA-TLX

To analyze the subjective mental workload changes between the two BCI experiments in Study 2 and 3, the participants were asked to answer the NASA-TLX questionnaire after each experiment (Hart & Staveland, 1988). Table 5.15 shows the NASA-TLX scores of both experiments for all subjects, and the results indicated that most of the participants' mental demand, temporal demand, effort, and frustration score increased in the second experiment compared to the first experiment, while performance decreased.

Table 5.15. NASA-TLX scores between two experiments

	Experiment	Mental Demand	Temporal Demand	Performance	Effort	Frustration
S01	1	9	7	16	19	9
	2	18	19	5	19	19
S02	1	13	11	16	14	3
	2	8	12	16	10	10
S03	1	11	13	17	15	2
	2	16	10	15	19	17
S04	1	17	2	11	17	11
	2	19	4	12	17	18
S05	1	19	15	7	15	17
	2	21	15	3	15	21
S06	1	10	5	19	7	2
	2	15	8	16	12	2
S07	1	9	2	14	11	2
	2	15	7	5	5	5
S08	1	13	3	11	14	1
	2	17	8	5	17	5

To test the significance of the differences between the experiments, a two-tailed Student's t-test was performed with the differences (scores of the second experiment – score of the first experiment) of each question. Table 5.16 shows that mental demand and frustration increased significantly, while performance significantly decreased compared to the first experiment.

Table 5.16. Results of t-test for each question

	Estimate	STD	t Ratio	Pr > |t|
Mental Demand	3.5	1.4516	2.41	0.0467*
Temporal Demand	3.125	1.574773	1.98	0.0876
Performance	-4.25	1.485044	-2.86	0.0243*
Effort	0.25	1.346291	0.19	0.858
Frustration	6.25	1.644797	3.8	0.0067*

5.8. Discussion

In Study 3, the feasibility of the proposed SMR-based BCI control FES system was validated with stroke and TBI patients in the semi-asynchronous experiments. Participants conducted the pre-determined tasks by following a fixed sequence, such as opening, stopping, grasping, holding, moving, and releasing a small ball by using the proposed SMR-based BCI-controlled FES system. To evaluate the proposed system, the effects of two IVs (the existence of FES and the application of the adaptive learning) on task performance (completion rate, accuracy, sensitivity, and ITR) were assessed. NASA-TLX scores from experiments in Studies 2 and 3 were also compared to analyze the changes of the subjective mental workload between the two experiments.

The feasibility of the proposed BCI-FES system

Study 3 investigated the feasibility of the proposed BCI-FES system under the semi-asynchronous mode not only for classifying a 2-class MI task in a single hand after detecting the existence of SMR but also for detecting the presence of MI-evoked SMRs when FES was activated. The results showed that the classification accuracy of the No-FES period, detecting the existence of SMR and classifying a 2-class MI task in a consecutive manner, after applying the adaptive learning method (61.9%; $t = 2.71$, $p = 0.0301$) was significantly higher than the true chance level (50.15% with 10 trials for both detecting SMR and classifying a 2-class MI task). However, the classification accuracy of the No-FES period before applying the adaptive learning method (49.4%) was not significantly higher than the true chance level (53.77%). In addition, the accuracies of decoding voluntary and passive SMRs for both learning types

(45.0% and 55.0%) was not significantly higher than the true chance level. Therefore, the null hypothesis of H3.1 could be rejected only in the No-FES period after applying adaptive learning, and in favor of the alternative hypothesis, which states that the classification accuracy of the No-FES period after applying adaptive learning is significantly higher than the true chance level. Although the classification accuracy of the No-FES period after applying adaptive learning was significantly higher than the true chance level, it did not achieve the threshold level (70%) for an effective control through a BCI system (Perelmouter & Birbaumer, 2000).

Some reasons to explain these results are as follows. First, the visual cues presented in synchronous experiments in Study 2 created an experimental environment that was different than for semi-asynchronous experiments in Study 3. During the experiments in Study 2, the video clips were provided to help participants mimic MI tasks, while there was no visual guidance in Study 3. Therefore, the patients might get confused target MI tasks or miss the timing of MI tasks during the semi-asynchronous experiment. The different decision-making procedures between could be another reason. For example, the experiment under the synchronous mode in Study 2 consisted of three classification periods, known as SMR, ACT, and FES periods, and the accuracies of SMR periods and ACT periods were separately analyzed. In contrast, in Study 3, SMR and ACT classifiers were combined in sequential mode under the semi-asynchronous mode. In this condition, the SMR classifier was for a go-no-go decision similar to a switch, and the ACT classifier classified between grasping and opening only if the SMR classifier determined ‘Go.’ Therefore, the accuracy of the final decision can be calculated by multiplying two probabilities. Thus, the expected accuracy of the combined

classifiers was 52.4% where the accuracies of SMR and ACT periods in Study 2 were 73.49% and 71.25%, respectively, which was similar to the actual accuracy of 52.8%. In addition, the difficulty of classifying a two-class MI task can explain low accuracy. For example, the results of the other study (Roset et al., 2014) using a 2-class MI task similar to this study showed that the classification accuracy of the offline analysis did not exceed the threshold level (70%).

In addition, the reasons for the low accuracy of classifying voluntary and passive SMRs can be explained similar to Study 2, such that (1) electrical artifacts from the FES might be not completely grounded; (2) the duration of the FES period might be too short, and (3) it was difficult to stay calm without movement-related imagination when FES was activated as a few participants mentioned.

FES existence type

The ANOVA results revealed that there were no significant main effects of the FES existence type on task performance, as well as any interaction effect between the FES existence type and learning type. Therefore, hypotheses H3.2 was not rejected. The results differed from the results in Study 2 in that the classification accuracy of the FES period with electrical stimulation was significantly lower than the SMR and ACT periods. One reason for the different results is that each experiment was performed in a different classification procedure as explained previously. As the final decision was made by sequentially combining the results from both SMR and ACT periods, the expected accuracy of the combined classifier (52.4%) decreased compared to that of each period. Furthermore, the maximum analysis time (6 seconds) might be too short to modulate SMRs during the detecting SMR period. Finally, the

sample size might be too small to have enough statistical power. Due to these reasons, the ANOVA results might not show any significant main effect of the FES existence type on task performance.

Learning type

The statistical analysis confirmed that the application of the adaptive learning method had a significant effect on the classification accuracy, and the post-hoc analysis showed that the application of the adaptive learning method significantly increased the accuracy similar to other studies (Vidaurre & Blankertz, 2010). However, other task performance, such as the completion rate, ITR, and sensitivity was not show any significant main effect of the learning type. Therefore, the null hypothesis of H3.3 could be rejected only for the classification accuracy, and in favor of the alternative hypothesis, which states that the classification accuracy after applying adaptive learning is significantly higher than before.

The difference in the experiment environment between offline (with visual cues) and online (without visual cues) experiments can explicate this effect. As the offline experiment utilized visual cues with fixed time intervals, the classifiers also affected the visual stimulus-evoked potential even after the intensive artifact removal procedures. With this effect, the classifier would not have worked normally in an online experiment without a visual cue. The ROC curves for each IV shown in Figure 5.6 also illustrate how the application of adaptive learning could be effective on the accuracy. The figures show that the biased curves were adjusted after applying the adaptive learning method. Possible reasons for the bias could be non-stationarity. Hazrati & Erfanian (2010) explained non-stationarity issues as follows.

"*Another important issue in designing an online BCI system is the machine learning to classify the brain signal which is characterized by significant day-to-day and subject-to-subject variations and time-varying probability distributions. (p730)*". For these reasons, the application of adaptive learning significantly increased the accuracy by addressing the gap from different environment and variations, and adjusting biased criteria by applying the most recent data.

However, other task performance such as CR, ITR, and sensitivity did not show any significant differences between the two learning types. One possible reason is that Yes-FES period had two different goals, such as stop FES as soon as possible and keep FES as long as possible. Thus, CR, ITR, and sensitivity might not represent the task performance of keep SMR. In addition, the electrical artifacts might impede the effect of adaptive learning.

Subjective assessment

The resultant NASA-TLX showed that most the participants' mental demand, temporal demand, effort, and frustration scores increased in the second experiment compared to the first, while performance decreased. The two-tailed Student's t-test results showed that mental demand and frustration significantly increased, while performance significantly decreased compared to the first experiment. These results also help to explain the low classification accuracy because higher mental demand and temporal demand cause mental fatigue, which results in lower performance (Fazel-Rezai et al., 2012). To address this issue, Rohm et al., (2013) set a series of exercises for participants to eat ice cream by MI and external device, and the authors confirmed that the workload was greatly reduced. These results suggested that the

BCI experiment should be more interesting, and, as suggested by the participants in the post-experiment questionnaire, an attempt to reduce the tedium and length of the MI training period may be necessary.

In the post-experiment questionnaire, some participants complained of either shoulder or upper arm muscle fatigue instead of the forearm. There are three possible reasons to explain shoulder muscle fatigue. First, the participants were asked to move their forearm to hold and move a ball during the experiment. In order to perform these sequential tasks, stretching movements of the upper arm and shoulder must be accompanied. These movement may lead to shoulder muscle fatigue because stretching movement could cause muscle pain due to the spastic muscles (Vuagnat & Chantraine, 2003). Another reason is that unnatural responses to FES might cause muscle fatigue. Although the current amplitude of FES was gradually increased by utilizing the ramp time function, some patient showed the retraction of the shoulder as an adverse reaction to electrical stimulation. This unnecessary tension of the body may have caused fatigue of the shoulder and upper arm muscles. Finally, this may be due to the awkward posture caused by the wires in the BCI-FES system which limited the movement of the patients.

6. GENERAL DISCUSSION

In this chapter, two general discussion topics were considered: BCI systems for a 2-class MI task in a single hand and a fixed sequence semi-asynchronous experiment.

6.1. SMR-based BCI Systems for a 2-class MI Task in a Single Hand

In this study, relatively new concepts of MI tasks were tested to build a novel SMR-based BCI system which could support a 2-class MI task in a single hand. Most SMR-based BCI research are categorized into two groups. The first group utilized SMR features to initiate a 1-dimensional application similar to an on/off switch (Blokland et al., 2014; Pfurtscheller et al., 2010), while the other group controlled a 2-dimensional application such as left/right, up/down, go/back motions of a robot, a wheelchair, a browser, and a game (Huang et al., 2012; Yu, Li, Long, & Gu, 2012; Yu, Li, Long, & Li, 2013). This is because the characteristic of the SMR features induced by MIs is most distinct only near the contralateral motor cortex in the left and right hemispheres.

Due to these limitations, the MI study has made many efforts to increase the classes (beyond left and right). A common example is the use of MI together with visual stimuli, also known as hybrid BCI, for browsers (Yu et al., 2012) or e-mail clients (Yu et al., 2013). In this case, a monitor that can display visual stimuli can be used without restriction because it is a required device of browsers or e-mail clients. However, it is not natural to use visual stimuli to control upper or lower extremities using an exoskeleton, orthosis, or FES. Also, it is awkward to employ imaginary movements of left and right hands to implement two

movements in a single hand. Therefore, it is very important to study the two movements in a single hand as in this study.

However, few studies explored distinct SMR features induced by different rhythmic MIs. Gu et al. (2009) investigated four MI tasks consisting of two MI types (wrist extension and rotation) and two speeds (fast and slow), and the authors reported that the speed variable had greater classification ability than the MI types. Similarly, Choi et al. (2016) employed slow-continuous and fast-transient MI tasks to classify a 2-class MI task in a single hand such as grasping or opening. Therefore, in this experiment, the different speed MI tasks were utilized to elicit the discriminative SMR patterns.

As the MI task is a mental imagination, clear MI instruction is essential for participants to follow different hand movements at the correct speed and timing. To address this issue, video clips were utilized to train the exact motion and speed to participants (Kim et al., 2016; Looned et al., 2014). Although visual cues explain the tasks easily, this method also has a critical issue that is a strong visual artifact as defined in Section 4.8.1. Therefore, elaborate removal methods are required.

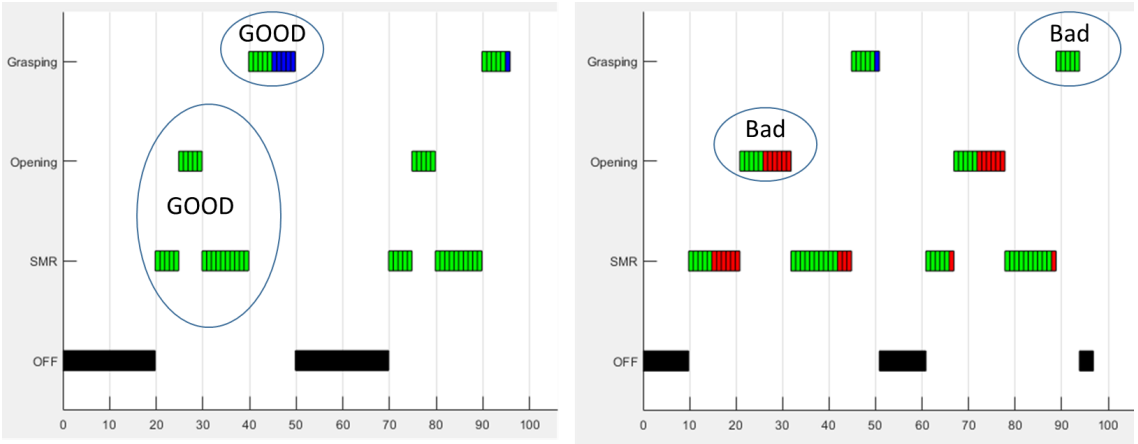
After participants had completed training, their brain signals were analyzed to extract two important features, such as the features to initiate the BCI system and to classify the MI tasks. In this study, the ERD/ERS and CSP methods were used with the sub-band division procedure. The advantages of the sub-band method are (1) the efforts for feature selection can be minimized by automated weighing techniques, and (2) wide frequency bands can be utilized. However, the disadvantage of this method is computational time because all combinations of frequency bands and channels (or time bins) should be separately classified.

In addition, to address the limitations of the SMR-based BCI such that (1) a long training period is required, and (2) classification accuracy of SMR is relatively lower than visual-based BCIs (Ortner et al., 2011), the ensemble method can be utilized by fusing multiple classifiers, such as LDA and SVM methods, to make one better and/or robust decision similar to this study.

Once the offline analysis is completed, the BCI system and algorithms should be tested under the online condition. Let's assume one moderate classifier which has 70% accuracies for both detecting SMR and classifying ACT will be used. Then, the expected accuracy for a certain target without error would be with a 49% chance (0.7 * 0.7 = 0.49) with a 30% chance in idle status (no SMR was detected), and a 21% chance in wrong status. If any mistake occurs, then the same procedure and chances will follow. For this reason, there is a great need for a new type of training and practical experiment methods that can alleviate this problem. For example, fixed sequence training under the semi-asynchronous mode which was proposed in this study.

6.2. Semi-asynchronous Mode

Figure 6.1 illustrates the results of good and bad trials. This diagram was also presented to the experimenter during the experiments, and it was not only useful in checking current performance of the participant during the experiment, but also facilitated examining the results after the experiment. The x-axis of the diagram shows time in seconds, and the y-axis displays the current FES status. Black boxes indicate the waiting time given at the beginning or between sequences. Green boxes indicate the time when the BCI system does not classify in the 5 seconds given immediately after performing the MI task between periods. Red boxes mean incorrect classification results, and blue boxes implies the time that successfully performed the keep-FES task. This box should appear for 5 seconds, meaning it was done perfectly without mistakes (5 correct decisions), unlike the red box.



(a) **(b)**

Figure 6.1. Graphical results of good and bad trials

The diagram on the left is an example of a successful trial that not only shows a balanced overall accuracy but also does not make any consecutive incorrect decisions. However, as an example of low performance, the right graph shows the successive failure of the opening-MI, and the FES system automatically performed the opening task in accordance with the 6-second maximum analysis time. In addition, the two green boxes at the top right indicate that the participant did not successfully perform keep-FES, and there is only one blue bar, meaning one-time success. Five seconds after the opening MI task was started, the participants should be in a calm state without any imagination to stop FES. Figure 6.1 (b) indicates that the stop-FES was not normally performed, since many red bars appear as shown in the figure.

However, under the complete asynchronous mode, it is difficult to know which timing shows the onset of MI by users due to the nature of the self-paced experiment. Furthermore, participants also get confused if errors are accumulated, and easily get frustrated with low performance, especially for disabled groups. Therefore, a novel experiment design was proposed that tried to achieve the advantages of both modes, by addressing the disadvantages of each. As a result, users successfully finished the experiment without excessive delay. Furthermore, the adaptive learning method also applied under the proposed mode which was not feasible or difficult to apply in asynchronous mode.

Thus, in this experiment, fixed sequence training in the semi-asynchronous mode was proposed. This mode has three important features which combined both synchronous and asynchronous methods as follows: (1) the sequence of tasks is fixed to clarify what the user should do; (2) error-free results to prevent them from being confused or exhausted, and (3)

utilization of SMR detecting initiation module similar to the asynchronous mode. Under the proposed semi-asynchronous mode, participants would be free from confusion and frustration. Furthermore, the experimenter could utilize the brain signal under the semi-asynchronous mode to enhance the classification algorithms by adjusting the classification parameters based on the most recent data, also known as adaptive machine learning (Pfurtscheller & Neuper, 2001; Vidaurre, Sannelli, et al., 2011; Wolpaw & McFarland, 2004).

The outcome of this study was the construction of a multi-class SMR-based BCI system with natural MI tasks, as well as restoring motor functions of disabled individuals. The results of Studies 2 and 3 were to address the low classification accuracy with electrical stimulation by applying the adaptive learning method under semi-asynchronous mode. The proposed experiment mode then plays an important role to bridge the gap between the two modes. Furthermore, this approach not only can improve task performance by minimizing misclassification rate but can also enhance user performance by increasing self-esteem and reducing frustration.

7. CONCLUSION AND FUTURE RESEARCH

7.1. Summary of Results

The objectives of this study were (1) to develop a novel SMR-based BCI-controlled FES with natural MI tasks for restoration of hand grasping and extension functions by identifying adequate electrode placement and user-specific FES parameters, and (2) to investigate the feasibility of the proposed system by evaluating the effects of the FES existence types and learning types on task performance, brain activity, and user satisfaction, while stroke and TBI patients performed a fixed sequence task representing ADLs.

This research consisted of three studies. Study 1 was to build an FES platform and to identify user-specific FES parameters that can minimize muscle pain and discomfort and consequently increase user satisfaction. Study 2 was to develop a novel SMR-based BCI system that can classify a 2-class MI task in a single hand by applying different rhythmic MI tasks. Finally, in Study 3, the proposed system was validated with fixed sequence training under semi-asynchronous mode.

The results showed that the application of a user-specific FES parameter significantly reduced perceived muscle pain and discomfort compared to a fixed parameter used in the previous studies. Furthermore, all participants were able to classify a 2-class MI task in a single hand by utilizing two different rhythmic MIs including SOG and FCO, and the ensemble classification method was able to classify a 2-class MI task significantly higher than the LDA method. Finally, the application of the adaptive learning method significantly increased the

classification accuracy of the proposed SMR-based BCI-controlled FES system with fixed sequence training under semi-asynchronous mode.

The results of NASA-TLX from Studies 2 and 3 showed that mental demand and frustration significantly increased, while performance significantly decreased compared to the first experiment. In addition, a few participants complained that they felt tired and had difficulty fully concentrating on the tasks during the post-experiment questionnaire. These results implicated that it is necessary to consider the subjective mental workload of participants in order to minimize confounding variables, such as the influence of tiredness and the subjective mental workload, in order to minimize the accuracy deterioration.

7.2. Contributions to BCI-FES Research

A few BCI research studies had investigated a 2-class MI by applying different MI task types such as different speeds and motions, and some research studies used FES systems for stroke and TBI patients. However, this study was one of the few studies to apply both the FES system and the BCI system with a 2-class MI task in a single hand for stroke and TBI patients. Furthermore, in this study, the semi-asynchronous mode with the fixed sequence was proposed that combines the advantages of both synchronous and asynchronous modes. The advantages of the proposed semi-asynchronous mode are (1) participants would be free from confusion and frustration because there is no error; (2) the experimenter can utilize the brain signals under the semi-asynchronous mode to enhance the classification algorithms, and (3) it is easy to change to two modes both synchronous and asynchronous with a small modification.

In addition, appropriate initial FES electrode positions were provided with respect to anthropometric data for each muscle motion, such as WF, WE, FF, and FE. These findings could address the lack of clear guidelines to determine FES electrode placement, and help novices without detailed knowledge of muscle anatomy to find adequate FES electrode placement. Furthermore, the systematic FES parameter setting procedure was proposed to identify user-specific FES parameters significantly for minimizing muscle pain and discomfort for user satisfaction.

7.3. Research Implications in Human Factor and Ergonomics

The outcomes of this study have four important HF/E implications. First, both the proposed FES platform and the SMR-based BCI system can be utilized as a test bed to investigate important HF/E topics such as effects of individual differences, environmental factors, task performance, and user satisfaction. Second, assistive technologies could be developed and connected to the SMR-based BCIs, such as robot controls, communication, and entertainment games, which would make it possible to explore multitudes of HF/E topics using BCI technology. Third, the SMR-based BCI-controlled FES systems can connect those with motor disabilities (e.g., stroke and TBI patients) to other people by greatly improving their quality of life, enhancing ADL capacity, and even increasing self-esteem. Finally, the results of the study are expected to be utilized to gain an understanding of neuroplasticity in musculoskeletal rehabilitation of stroke and TBI patients in clinical studies.

7.4. Research Limitation and Future Work

The main limitation of this study was that the sample size was too small to have enough statistical power. If additional experiments are in progress, some main effects that we concluded to be not significant are likely to change. The small sample size also prevented the expansion of the study, such as investigating differences in performance according to severity, and differences between stroke and TBI patients.

The classification accuracies during the FES period for both asynchronous semi-asynchronous experiments were not higher than the true chance level, and it implies that the proposed SMR-based BCI system could not distinguish between voluntary MI-evoked SMRs and FES-driven passive-movement-evoked SMRs. There are three possible reasons to explain this low accuracy. First, when FES was activated, the electrical artifacts might be not completely grounded by the anti-static wrist strap applied to the opposite hand of the affected forearm. Thus, it is possible that electrical stimulation was mixed with the EEG signals, making it difficult to classify. Second, these passive movements driven by FES might have prevented the patients from stopping the MI tasks, as some participants mentioned that it was difficult to stay calm without movement-related imagination when FES was activated. Finally, although the participants were asked not to perform any voluntary physical movements during the experiments, they might simultaneously perform spontaneous movements by following the FES-driven motion. Since EMG signals were not measured in this study, it was not known whether the motion had progressed. Therefore, this limitation should be solved through further study.

Although the classification accuracy of No-FES period after applying adaptive learning under semi-asynchronous mode was significantly higher than the true chance level, it did not achieve the threshold level (70%) for an effective control through a BCI system (Perelmouter and Birbaumer, 2000). Moreover, the adaptive learning method significantly increased the accuracy similar to other studies (Vidaurre & Blankertz, 2010), but these results might be due to an order effect that the participants were accustomed to the semi-asynchronous experiment while continuing to conduct the experiment.

The other limitation was that adequate FES electrode placement was altered during supination and pronation, leading to sharp muscle pain. Participants were asked to minimize supination and pronation to prevent any muscle pain and discomfort, however, this restriction made their movement unnatural. As Keller & Kuhn (2008) reviewed, the array types of FES electrode are available, which could help to solve this issue by synchronizing between supination (pronation) and the electrode onset in real-time.

Finally, this study did not consider the reinforcement or attenuation of SMRs over the time. It might be possible to identify the change of SMRs as the time progressed while conducting a long-time experiment, and the relationship between the time and MI task performance could be evaluated to determine the proper duration of the SMR-based BCI experiment with respect to the fatigue and tiredness of participants. In this way, task performance can be maximized, and attention deterioration minimized.

APPENDICES

Appendix A. FES Safety Screening Questionnaire

(Modified from Reed (1997), Jones and Johnson (2009), and Rennie (2010))

The following items may be harmful to you in functional electrical stimulation treatment. Please provide a "yes" or "no" answer for every item.

YES	NO	
☐	☐	Unstable cardiac conditions
☐	☐	Cardiac pacemaker or implanted cardioverter defibrillator/ICD
☐	☐	Internal electrodes or wires (pacing wires, DBS or VNS wires)
☐	☐	Implanted drug pump (for chemotherapy medicine, pain medicine)
☐	☐	Ear (cochlear) implant, middle ear implant
☐	☐	Acute danger of Hemorrhage
☐	☐	Acute danger of Thromboembolism
☐	☐	Tuberculosis
☐	☐	Epilepsy
☐	☐	Skin disease
☐	☐	Hyper/hypotension
☐	☐	Impaired cognition
☐	☐	Impaired communication
☐	☐	Impaired circulation
☐	☐	Malignancy
☐	☐	Decreased sensation
☐	☐	Dysesthesia

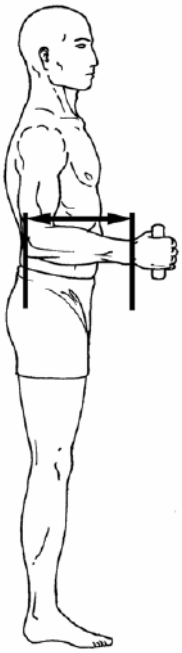
Female Patients: Are you pregnant? YES ☐ NO ☐

Appendix B. Anthropometric Data for Elbow-Wrist Length

(Retrieved from Gordon et al. (1989))

Elbow-Wrist Length

FEMALE N = 2208			MALE N = 1774		
Centimeters		Inches	Centimeters		Inches
26.25	Mean	10.33	29.03	Mean	11.43
1.54	Std Dev	.61	1.54	Std Dev	.61
33.40	Maximum	13.15	35.00	Maximum	13.78
17.00	Minimum	6.69	22.60	Minimum	8.90
	Percentiles			Percentiles	
22.94	1st	9.03	25.79	1st	10.15
23.26	2nd	9.16	26.09	2nd	10.27
23.47	3rd	9.24	26.30	3rd	10.35
23.78	5th	9.36	26.60	5th	10.47
24.28	10th	9.56	27.09	10th	10.66
24.64	15th	9.70	27.44	15th	10.80
24.93	20th	9.81	27.72	20th	10.91
25.18	25th	9.91	27.97	25th	11.01
25.41	30th	10.00	28.19	30th	11.10
25.62	35th	10.09	28.40	35th	11.18
25.83	40th	10.17	28.60	40th	11.26
26.03	45th	10.25	28.80	45th	11.34
26.22	50th	10.32	28.99	50th	11.41
26.42	55th	10.40	29.18	55th	11.49
26.62	60th	10.48	29.38	60th	11.57
26.83	65th	10.56	29.58	65th	11.65
27.05	70th	10.65	29.80	70th	11.73
27.29	75th	10.74	30.03	75th	11.82
27.56	80th	10.85	30.30	80th	11.93
27.86	85th	10.97	30.61	85th	12.05
28.26	90th	11.12	31.01	90th	12.21
28.83	95th	11.35	31.61	95th	12.45
29.21	97th	11.50	32.02	97th	12.61
29.49	98th	11.61	32.33	98th	12.73
29.93	99th	11.78	32.84	99th	12.93



ELBOW-WRIST LENGTH

The horizontal distance between the posterior point of the right elbow flexed 90 degrees and the stylion landmark on the right wrist of a subject standing with the forearm and hand held horizontally is calculated as follows: FOREARM-HAND LENGTH minus HAND LENGTH.

Appendix C. Anthropometric Data for Circumference of Forearm

(Retrieved from Gordon et al. (1989))

FEMALE

CENTIMETERS		INCHES
25.37	MEAN VALUE	9.99
.03	SE(MEAN)	.01
1.51	STD DEVIATION	.59
.02	SE(STD DEV)	.01
32.50	MAXIMUM	12.80
21.00	MINIMUM	8.27

SYMMETRY---VETA I = .30
KURTOSIS---VETA II = 3.54
COEF. OF VARIATION = 5.9%
NUMBER OF SUBJECTS = 2208

THE PERCENTILES

CENTIMETERS		INCHES
21.99	1ST	8.66
22.40	2ND	8.82
22.65	3RD	8.92
22.99	5TH	9.05
23.51	10TH	9.26
23.85	15TH	9.39
24.13	20TH	9.50
24.36	25TH	9.59
24.57	30TH	9.67
24.77	35TH	9.75
24.95	40TH	9.82
25.13	45TH	9.89
25.31	50TH	9.97
25.50	55TH	10.04
25.68	60TH	10.11
25.87	65TH	10.19
26.08	70TH	10.27
26.31	75TH	10.36
26.57	80TH	10.46
26.88	85TH	10.58
27.29	90TH	10.75
27.94	95TH	11.00
28.38	97TH	11.17
28.73	98TH	11.31
29.30	99TH	11.54

MALE

CENTIMETERS		INCHES
30.35	MEAN VALUE	11.95
.04	SE(MEAN)	.02
1.88	STD DEVIATION	.74
.03	SE(STD DEV)	.01
37.20	MAXIMUM	14.65
23.30	MINIMUM	9.17

SYMMETRY---VETA I = .24
KURTOSIS---VETA II = 3.29
COEF. OF VARIATION = 6.2%
NUMBER OF SUBJECTS = 1774

THE PERCENTILES

CENTIMETERS		INCHES
26.29	1ST	10.35
26.78	2ND	10.54
27.08	3RD	10.66
27.47	5TH	10.81
28.06	10TH	11.05
28.45	15TH	11.20
28.77	20TH	11.33
29.05	25TH	11.44
29.31	30TH	11.54
29.55	35TH	11.63
29.78	40TH	11.72
30.01	45TH	11.82
30.24	50TH	11.91
30.48	55TH	12.00
30.72	60TH	12.10
30.98	65TH	12.20
31.25	70TH	12.30
31.56	75TH	12.42
31.90	80TH	12.56
32.31	85TH	12.72
32.83	90TH	12.93
33.61	95TH	13.23
34.11	97TH	13.43
34.47	98TH	13.57
35.02	99TH	13.79

FOREARM CIRCUMFERENCE, FLEXED

The circumference of the flexed right forearm is measured with a tape passing across the crease at the juncture between the upper arm and the forearm. The measurement is made in a plane perpendicular to the long axis of the forearm. The subject stands with the upper arm extended forward horizontally, the elbow flexed 90 degrees, and the fist tightly clenched and held facing the head.

Appendix D. Guideline for Proper Skin Preparation

(Retrieved from Axelgaard Manufacturing's (Axelgaard Manufacturing Co., n.d.))

- Before electrodes are placed, inspect the skin thoroughly to be certain that there are no small abrasions or openings. These openings would serve as pathway of current and will become very uncomfortable for your subject.
- If the skin is very hairy it may need to be shaved, but this should the day before the first stimulation session as shaving will cause points of irritation and this will cause patient to be uncomfortable during the stimulation session.
- An alternative to shaving the day before would be to use scissors to clip the hair as close to the skin as possible, being careful not to abrade the skin.
- Clean thoroughly the skin of any lotion, oils, makeup, and dead skin with either a wet towel or alcohol.
- Make sure the skin is dry before the electrodes are placed.
- Place the electrodes in the predetermined location, making sure that lead wires move away from the joint angles, and that electrodes are smooth on the skin with no wrinkles.
- Place lead wires into electrodes, being certain of polarity.
- Once the system is set, turn the stimulator on and slowly advance the amplitude according to patient's tolerance.

Appendix E. Post-Experiment Questionnaire

1. At any point in the study (including right now), did you feel pain, numbness, fatigued, or any other sort of general discomfort? If so, please explain:

2. Overall, how much were you satisfied with the experiments on this study?

   ◯ Very satisfied

   ◯ Somewhat satisfied

   ◯ Neither satisfied nor dissatisfied

   ◯ Somewhat dissatisfied

   ◯ Very dissatisfied

3. Please feel free to provide any additional comments you may have about the features used in the SMR-FES BCI system:

Appendix F. NASA Task Load Index

(Modified from http://humansystems.arc.nasa.gov/groups/TLX/downloads/TLXScale.pdf)

"Physical Demand" is excluded.

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?

Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?

Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?

Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?

Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?

Very Low — Very High

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